UNITED STATES DISTRICT COURT
WESTERN DISTRICT OF WASHINGTON
AT SEATTLE

KATHERINE MOUSSOURIS, et al.	)	
Plaintiffs,	)	
v.	)	Case No. C15-1483JLR
MICROSOFT CORPORATION,	)	
Defendant.	)	

EXPERT REPORT OF ALI SAAD, PH.D.

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ASSIGNMENT

1. I was retained by counsel for defendant Microsoft Corporation to respond to the expert report submitted by Dr. Henry Farber on behalf of Plaintiffs in the case of *Katherine Moussouris, et al. v. Microsoft Corporation*. Plaintiffs allege that the company has engaged in a "pattern, and practice of sex discrimination against female employees in technical and engineering roles, including technical sales and services positions ("female technical employees") with respect to performance evaluations, pay, promotions, and other terms and conditions of employment."[1] I was provided with electronic human resources data, payroll data, performance review system data, and other documents related to Microsoft, including depositions and company policy documents, in order to conduct my assignment. My report responds to the analyses and opinions summarized in Dr. Farber's report and associated backup materials, as well as his deposition testimony. I may supplement this report at a later date if additional relevant information is made available to me.

QUALIFICATIONS

2. I am the Managing Partner of Resolution Economics Group LLC, a firm whose activities include performing economic and statistical analyses in connection with litigation and other consulting matters. Before beginning my consulting career I was in academia as a member of the faculty of the economics and finance department at Baruch College of The City University of New York. While there I taught labor economics, micro and macroeconomics, econometrics,

[1] *Second Amended Class Action Complaint, in the matter of Katherine Moussouris, Holly Muenchow, and Dana Piermarini, on behalf of themselves and a class of those similarly situated, v. Microsoft Corporation*. United States District Court, Western District of Washington, Case No. 15 cv 1483 (JLR), filed 04/06/16, ¶1.

and economic history. In connection with my consulting, I have extensive experience providing statistical and economic analyses in connection with class action employment cases, including employment discrimination and wage and hour matters, and I have also published and lectured on these topics. A particular focus of my work has been in statistical analysis related to claims of systemic gender discrimination. I also have significant experience in analyzing complex data for the purpose of assisting counsel in evaluating class certification and liability. I hold a Ph.D. in Economics from The University of Chicago, and a B.A. degree in History and Economics from The University of Pennsylvania. I have been qualified as an expert witness in both Federal and State Courts. My resume, including all publications and testimony over the past four years, is attached to this report as Attachment A. My firm bills for my services at my current hourly rate of $650 per hour.

DATA AND DOCUMENTS RELIED UPON

3. I was provided by Counsel with databases, depositions, and other documents. In addition, I collected Census and other publicly available data, and relied on additional secondary materials. The materials I reviewed and relied upon for my analysis and opinions are listed in Attachment B.

INTRODUCTION AND SUMMARY OF FINDINGS

4. Plaintiffs allege in their Second Amended Complaint that there is a “continuing policy, pattern and practice of sex discrimination against female employees in technical and engineering roles, including technical sales and services positions (“female technical employees”) with respect to performance evaluations, pay, promotions, and other terms and conditions of

employment."[2] Dr. Farber submitted a report that summarized his analyses of compensation, promotions, and performance ratings. The analyses were conducted at an aggregated level, meaning that each of the analyses was designed to identify an overall bottom line finding. When asked why he did not study variability in the outcomes with respect to his pay and promotion analyses of the Microsoft data, he testified at deposition that "I did not take that as my assignment. My assignment was to examine whether there was a pattern at Microsoft of differences in compensation and promotion rates, which is what I did, and I uncovered the patterns."[3] By "patterns," he appears to mean by how much *on average* women are paid less than men and what the shortfall was *overall* in promotions over the period of time he analyzed.[4] Identifying an aggregate "pattern" does not speak to whether or not the finding applies in a statistically consistent manner across putative class members and decision makers, or, in this highly complex and diverse business setting, across the wide variety of work settings represented in the data. To use the word "pattern" in the way Dr. Farber does is misleading in that is connotes there is something consistent among the experiences of the putative class members, which as will be seen, is not the case.

<u>Dr. Farber's aggregated analyses contain a great deal of underlying variation in outcomes along many dimensions</u>

5. In order to respond to Dr. Farber's flawed aggregate studies, I have also conducted studies at the aggregated level, and as I demonstrate, his "pattern," as he referred to it in deposition, of a bottom line adverse finding in both pay and performance is not supported once the analyses are conducted correctly. However, before I describe my aggregated findings, I will

[2] Second Amended Complaint, page 1, ¶ 1.
[3] Deposition of Dr. Henry Farber, 282:17-283:3.
[4] Deposition of Dr. Henry Farber, 284:9-11, 286:19-22.

first use Dr. Farber's data and analytical approaches alone to demonstrate how much variability in outcomes is present in the data underlying his aggregated models. For example, in one of his pay analyses, Dr. Farber identifies a pay shortfall for women of 2.8%, which applies as an average result across all years and all of the employees he studied. It is certainly not the case that every single woman experienced a pay shortfall of 2.8%. An analyst would not expect to find that. However, it is important to explore the extent to which different women depart from the 2.8% average: for example, how many are found by Dr. Farber's model to be paid more than expected and by how much, how many are paid less than expected, and by how much, and so on. It is also important to explore the extent to which variations in the outcomes of Dr. Farber's aggregated and commonly applied statistical models are found when they are applied at the decision maker level. Dr. Farber does not conduct any analyses of the statistical outcomes by decision maker, even though Plaintiffs allege that decision makers at Microsoft are the actors that behave in a common and adverse manner toward female employees.

6. In addition to decision maker and individual putative class member variations, there is also considerable variety in outcomes for putative class members occupying the two professions that Dr. Farber examines. For example, in IT Operations, *no average pay difference* is found based on Dr. Farber's model. Women working in a profession that experienced *no average pay difference* cannot be said to have an adverse pay difference in common with members of a profession that *does* exhibit an apparent pay difference according to Dr. Farber's model. It is these types of issues which are left unexplored by Dr. Farber, who only examines bottom line, aggregated average results.

7. Turning to his analysis of promotions, Dr. Farber's reliance on a single model to describe outcomes for all women obscures the fact that when his analytical model is applied to IT

Operations alone, there is no promotions shortfall for women working in that profession. And for women working in the Engineering profession, Dr. Farber's approach shows that there is no aggregate shortfall for promotions that take place during the annual review, which constitute almost [redacted] of all promotions. And using Dr. Farber's model to examine promotion outcomes at the supervisor or decision maker level indicates that supervisors vary widely in the extent to which the women they supervise are promoted at higher or lower rates than expected. These and other similar findings are inconsistent with Dr. Farber's assertion that his aggregated statistical results represent a "pattern" (by which a common practice with an accompanying common resolution is implied) by Microsoft decision makers.

8. The first section of my report examines the variability that Dr. Farber ignored by constructing highly aggregated "one size fits all" models of pay and promotion. I will use Dr. Farber's data and analytical models to demonstrate the variability underlying his aggregated results, without making any corrections to his analytical models. The second section of my report will deal with the flaws I find in Dr. Farber's analytical approach, and in that section I will show that even if the data are aggregated, the bottom line findings are that there are no meaningful differences in pay or promotion outcomes for women. In addition, my analysis of performance ratings during the class period agrees with Dr. Farber's: there is no difference between men and women in job performance ratings. A summary of my findings regarding the variations contained within Dr. Farber's aggregated analyses is as follows:

- The focus of Dr. Farber's regression analyses of compensation is a single regression coefficient on the female variable, which represents the average percentage difference between the pay of men and women.

- This single measure represents only an average, and obscures considerable variety churning below the surface.

- Dr. Farber's pay studies put all employees together in a series of regression models that combine the data for all years, all locations, all business areas, and within the scope of the class Plaintiffs seek to certify, all types of jobs and all levels of skill and performance.

- Total compensation for this group of employees ranges over the class period from approximately [redacted]

- These employees occupy 278 Standard Titles over the class period, work on dozens of different product lines, work in 45 states, have education ranging from high school graduate to a double Ph.D., and report to hundreds of different supervisors.

- Taking Dr. Farber's analyses at face value with no corrections for their flaws and examining this underlying variation in outcomes for putative class members reveals that many women earn more than Dr. Farber's regression model predicts, many earn less than his model predicts, and many earn what his model predicts.

- When Dr. Farber's results are examined by the decision makers/supervisors who are responsible for pay and other employment decisions, there is wide variety across supervisors regarding pay outcomes for women.

- At the decision maker level, there are supervisors under whom there are no women with statistically significant adverse pay differences according to Dr. Farber's results, and they supervise many women.

- Some supervisors' outcomes are a combination of "over" and "under" payment, some show no "over" payment, some show no "under" payment and many show neither.

- There is little consistency when examining Dr. Farber's statistical pay results by supervisor.

- Applying Dr. Farber's model of compensation, neither Plaintiff Moussouris nor Plaintiff Muenchow was paid significantly differently from what Dr. Farber's model predicts for them.

- Six of the nine declarants submitted by Plaintiffs in connection with their motion for class certification are paid more than expected based on their characteristics as measured by Dr. Farber's model. None of the declarants was paid significantly less than expected, and one (Plaintiff Dove) was paid significantly more than expected in every year under Dr. Farber's model.

- Dr. Farber's promotion studies are also aggregated, and result in single measures such as an overall shortfall in promotions or a regression measure of the difference in female promotion probability.

- Dr. Farber's promotion models are also highly flawed, but taking them at face value and examining the variations in outcomes reveals wide variation in the outcomes for women by decision maker/supervisors.

- There are supervisors who promote more women than Dr. Farber's model predicts and others who promote fewer than expected numbers of women. The range of the "under" and "over" promotions is wide – both statistically significant "under" and "over" outcomes are seen. Dr. Farber's model does not provide a common answer to the question of female promotions that links outcomes to decision makers.

Dr. Farber's aggregated models contain many flaws and when the analysis is properly conducted, there is virtually no difference in either pay or promotions for women

9. The second section of my report takes a closer look at Dr. Farber's analyses to show that even in the aggregate, Dr. Farber's statistical models are flawed and misleading. As a threshold matter, Dr. Farber does not note that his finding of no gender differences in performance ratings directly contradicts Plaintiffs' theory of the case. According to Plaintiffs, biased performance evaluation procedures that "systematically undervalue female technical employees"[5] were the presumed common practice causing adverse pay and promotion outcomes, because pay and promotions are linked to performance.[6] Because both Dr. Farber and I have found no gender differences in performance rating outcomes, this causal link cannot be established. Dr. Farber does not point to any other policy or provide any other explanation for the pay and promotion differences he claims to have found. As I will show, the reconciliation of unbiased performance rating outcomes and the observed pay and promotions of women is that once Dr. Farber's flawed models are corrected, there is also no statistical evidence of meaningful gender differences in either pay or promotions.

[5] Second Amended Complaint, page 5, line 14.
[6] See also the Responses to the First Set of Interrogatories by Moussouris and Muenchow.

10. In his pay analyses, Dr. Farber does not take into account important factors that serve to explain differences in pay regardless of gender, and which also reduce the measured female pay differential to practical insignificance – only 0.4% instead of the 6.3% or 2.8% of his Models 4 and 5. In his promotion analyses, Dr. Farber fails to control for important factors influencing promotion, which are tenure in current level and tenure in current title, and instead controls only for total time at Microsoft, which is less relevant when the company is considering moving an employee from one level to the next. In his promotion analyses he also fails to take into account the timing of promotions during the year, which has a meaningful impact on the analysis, and he fails to incorporate decision makers into his statistical model. Dr. Farber also does not restrict his promotion analysis to the class period. The latter fact alone reduces his finding of a female shortfall of 518 to 337, with no other changes to his approach. And when this and other changes are made, Dr. Farber's shortfall of 518 drops to only 79 promotions, which again, is practically speaking insignificant given that 4,300 actual female promotions occurred over the class period.[7]

11. More specifically regarding his pay analysis, Dr. Farber dismisses the use of Career Stage as a control variable in his pay models because he believes that it is accounted for by using Standard Titles. I will show that this assumption is incorrect and has a substantial effect on his estimates. Dr. Farber also dismisses the use of Stock Level as a control variable, which he claims is simply a pay band. On its face, this is inconsistent with his analysis of promotions, in which promotions are defined by him as a move from one Stock Level to the next. Moving from

[7] I will make frequent reference to the concepts of both "statistically significant" and "practically significant" (i.e., "meaningful") throughout this report. Both of these concepts are relied upon by labor economists when they study empirical phenomena. There are times when a tiny measured difference is statistically significant because a very large number of observations or data points are in an analysis, and there are times when a large measured difference is not statistically significant because relatively few data points are analyzed. There is a substantial literature, including guidance in the *Reference Manual on Scientific Evidence* that cautions against exclusive devotion to the doctrine of one of these concepts over the other in all circumstances. I will discuss this issue in greater detail below.

one Stock Level to the next is accompanied by meaningfully higher levels of responsibility and involves the application of skills at a higher level. This is extensively documented in the materials produced during discovery in this case, as I will show. In his deposition, Dr. Farber stated that perhaps Microsoft moves people to higher Stock Levels simply in order to pay them more. This statement does not represent sound economic logic. Companies do not typically increase pay beyond simple cost of living adjustments unless there is a productivity based reason to do so. Second, given the wide range of pay within each Stock Level, it is easy to increase pay significantly within a Stock Level at Microsoft. It is not necessary to promote someone from one level to the next in order to raise their pay because the pay range at each level is quite wide. Rather, the move from one level to the next is an increase in job scope and responsibility and is defined by Microsoft as a promotion, not simply a pay raise.

12. I incorporate these factors into Dr. Farber's pay and promotions analyses to show that there are distinct groups of women at Microsoft who do not experience any adverse pay and promotions outcomes.

13. In the aggregated analyses I summarize, there are instances where very small differences in outcomes remain statistically significant. For example, a 0.4% pay difference is found to be statistically significant, which is due to the enormous sample sizes involved. I discuss at many points that such a small difference is not practically or economically significant. However, it is also important to note that it is entirely likely that even these small differences in pay and promotions would themselves be explained by variables that continue to be omitted from my analysis, because they are not available in the data produced. For example, I will show below that Dr. Farber's failure to include variables that *are* in the data serve to reduce the measured pay difference between men and women. Leave of absence is one such variable which Dr. Farber

does not include in his analyses. I also discuss that prior work experience is not available in the data, yet may and likely does differ in ways that correlate to gender. Since employers typically take into account the prior experience of new hires recruited from other employers – referred to as lateral hires in the analyses below – then not having this information in the analysis would bias upwards the finding of measured differences between men and women if men tend to have greater amounts of relevant prior experience. Thus, even though I show quantitatively very small remaining differences in both promotions and pay for certain subsets of employees, even these small differences could be due to omitted variables, not to gender.

14. To summarize my findings regarding overall analyses of performance, pay and promotions, I find that:

- There is no difference between performance ratings of men and women overall during the class period. Dr. Farber also finds no difference in the performance ratings between men and women within the class period.
- Contrary to the statements of Plaintiffs in their SAC, I also find no evidence that women are adversely downgraded during the calibration process relative to men.
- There is no statistical support for Plaintiffs' allegation that the process of performance evaluation is biased against women and is causal to adverse pay and promotions outcomes.
- The fact that there is no gender difference in the performance evaluation outcomes is inconsistent with Plaintiffs' claims that Microsoft evaluation procedures "undervalue female technical employees." Performance evaluation is an explicit process whereby decision makers at the company are asked to place a value on each employee's work through a rating.
- Dr. Farber's statistical models of pay and promotion contain serious flaws, which when corrected, eliminate or reduce to very small levels any differences between men and women in both pay and promotions.
- Dr. Farber states in his report that "Economists define sex discrimination in pay to be differences in pay between men and women that cannot be explained by differences in productivity-related characteristics like work experience or differences in the type of

work they perform."[8] Dr. Farber reiterated this principle at his deposition. Dr. Farber does not in fact fully take account of "the type of work" performed by employees, because he fails to use in his analyses several of the variables in the Microsoft data which relate to "productivity-related differences" and "type of work."

- Dr. Farber's statistical models do not "similarly situate" employees because they do not take into account all relevant job-related characteristics and consequently his analytical results inappropriately attribute differences in pay and promotion to gender when in fact they are due to other non-gender characteristics.

- A failure to control for type of as well as the level of skill and responsibility related to work performed leads Dr. Farber to incorrectly conclude that women are underpaid relative to men. Dr. Farber's control for "type of work" is only the category or the *occupation* of the employee, such as "software engineer."

- There were employees during the class period whose Standard Title was software engineer at Microsoft who made [redacted] and those who made over [redacted]. This enormous range is likely due to differences in the extent of expertise and skill among these employees. At Microsoft there is a variable called "Stock Level" which captures these differences.

- Dr. Farber asserts that "Stock Level" is just another way to measure pay, and for this reason it should not be included in a pay analysis.

- However, Stock Level is used by Dr. Farber as the definition of promotion, which means a change in the content of work in terms of the levels of skill and scope of responsibility. By omitting altogether Stock Level from his analyses, Dr. Farber fails to "similarly situate" the employees in his analysis.

- There is extensive documentation in the Microsoft materials contemporaneously generated by evaluating managers of the fact that different Stock Levels separate employees into different skill and responsibility bands, within "Standard Titles."

- To omit Stock Level from a pay regression, when the evidence supports the notion that Stock Level measures different skill and responsibility levels within occupational groupings, causes Dr. Farber's pay models to be biased, and to overstate the gender pay difference.

- In addition, Dr. Farber's pay analyses omit a number of other relevant variables, such as prior experience, leaves of absence, part time status, and whether hired from college or laterally from other companies.

[8] Report of Dr. Henry Farber, page 14, para 30.

- When the aggregated pay analyses are correctly performed with the available data, the pay difference Dr. Farber measures, which he claims is no less than 2.8% falls to 0.4%.

- A pay difference under 1% is extremely small, and fails to achieve what economists refer to as “practical significance. The only reason that a 0.4% difference is statistically significant in the analyses in this case is because there are approximately 120,000 observations in the analysis, such that even very small differences are likely to be found statistically significant.

- Dr. Farber also claims that Stock Level is “tainted” because he claims that women advance to higher Stock Levels at lower rates than men, and therefore he declines to use Stock Level in his pay analyses. However, this approach is not justified by his promotions models, which show a relatively small shortfall in promotions. Throwing out the entire Stock Level variable when there is a small shortfall under Dr. Farber’s own model is unsupportable.

- Although I ultimately disagree that Stock Level is tainted in a meaningful way or even at all, I have addressed Dr. Farber’s claim of “taint” in Stock Level, which he says arises due to a shortfall in promotions, by taking his stated shortfall in promotions and simulating what the Stock Levels for men and women “should have been” under his assumptions and then re-estimating the pay model using Stock Level as a control.

- Dr. Farber applies his promotions analysis beyond the class period. Consequently, his analysis concludes there is a female shortfall of 518, when applying the same model to the class period results in a shortfall of 337.

- Dr. Farber does not capture in his promotions analysis the fact that Microsoft promotions occur pursuant to an annual review, to a mid-year review, and at other times of the year. Dr. Farber instead focuses only on changes in Stock Level observed by comparing Stock Level of each employee at adjacent year ends.

- Dr. Farber does not separate his promotions analysis by Engineering and IT Operations professions, which is important because there are fundamentally different promotion levels involved in the two different professions.

- Dr. Farber fails to control for important tenure variables in his promotion analysis, which are time in current level and time in Standard Title. Thus, his model treats as the same two employees with 7 years at Microsoft who share a particular Stock Level and Standard Title, but one has been in the position 6 months and the other for 3 years.

- Dr. Farber fails to take into account that promotions are recommended at the local supervisor level. He does not control for the actual decision making process.

- When the correct time period is analyzed, the correct tenure variables are used, and decision makers are factored into the analysis, the shortfall in promotions falls to 90, which represents 98% of what was expected.

- This tiny difference is substantively (or "practically") insignificant.

- While not a statement about statistical significance, EEOC guidelines on selection practices state that when selection rates for a protected group (women) are less than 80% of selection rates for a benchmark group (men), there is a potential cause for concern regarding the selection practice in question. Female selections for promotion for the employees at issue in this case are 98% of the selection rate for men.

- Breaking down the promotions analysis by professions, there is no female shortfall in promotions for IT Operations employees. There is a small shortfall in Engineering. If the insignificant shortfall in Engineering during the annual review period is removed from the shortfall total, there remains only a statistically significant shortfall of 79 promotions in Engineering.

- Breaking down the time periods during each year, there is no shortfall under the annual review period for either IT Operations or Engineering, which comprises [redacted] of all promotions.

15. I turn next to a brief discussion of the Microsoft population being analyzed, and then to a more detailed discussion of the variations that are found under the surface of Dr. Farber's aggregated analyses.

OVERVIEW OF THE POPULATION

16. In June 2012, Microsoft employed about 55,000 people in the U.S., a figure which rose to 63,000 by June 2016.[9] In the present matter, there are 8,092 women in the putative promotions class, defined as women employed in Engineering or IT Operations in Stock Levels 59 to 64 at any time during the period 9/16/2012 through 9/30/2016, which is the end of the data produced in this case. Of these 8,092 women, 2,679 (33.1%) were former employees as of 9/30/2016. Also, 1,629 of the 8,092 (20.1%) were Managers at least once in the class period according to

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[9] Microsoft's US Security and Exchange Commission Form 10-K filings, 2012 and 2016.

their Career Stage as indicated in the data, and 2,955 (36.5%) were either Leads or Managers, similarly defined. 180 were designated "manager of managers."[10]

17. In the putative pay class, defined by Plaintiffs as women employed in Engineering or IT Operations in Stock Levels 59 to 67, there are 8,691 women, of whom 2,889 (33.2%) were former employees as of 9/30/2016. According to their Career Stage designation, 2,126 (24.5%) were Managers at least once in the class period, and 3,457 (39.8%) were either Leads or Managers. 472 were designated as "managers of managers."[11]

18. Named Plaintiff Ms. Moussouris had three female direct reports during the class period who are putative class members. Ms. Muenchow was supervised by three putative class members.

19. There were 278 different standard job titles in use during the class period for two different professions, across 24 disciplines. Employees worked in 45 states, and ranged in age from 18 to 79. Their annual base salaries ranged from almost [redacted] and their total annual compensation ranged from about [redacted].

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[10] This is based on a variable in MS People called "Manager_Of_Managers_Ind."

[11] Dr. Farber's data extends back to 2010, and his analyses inexplicably include that pre-class period data. From 9/16/2012 to 5/31/2016 (when his data end), there were 8,072 women in the putative promotion class, of whom 2,679 were former employees as of 5/31/2016. There were 1,588 whose Career Stage indicated they were ever a Manager, 2,926 were either Leads or Managers based on Career Stage, and 168 were "manager of managers." My class size estimate is slightly higher than his, because Dr. Farber relies on effective date to count class members, and I build a daily incumbent file first and only then restrict it to the class period. (For example, he would not count someone in the class who had a transaction date of 9/5/2012 in Engineering and switched to Business on 11/19/2012, because her first transaction date inside the class period is in November 2012. Also, he included two people whose termination date was 9/16/2012, but I excluded them assuming their last work day would have been 9/15/2012.) In the corresponding putative pay class in Dr. Farber's data, there were 8,668 women, of whom 2,889 were former employees by the end of his data. There were 2,079 whose Career Stage indicated they were ever a Manager, 3,423 who were either a Lead or Manager according to their Career Stage, and 457 "manager of managers."

DR. FARBER'S AGGREGATE ANALYSES OBSCURE CONSIDERABLE VARIATION AMONG WOMEN

20. It is my understanding that part of my task is to examine from a statistical perspective whether there are patterns in pay and promotion outcomes that are common to the putative class, or whether they are so widely varying in character that they may not arise due to specific common practices, to which common answers would apply. Dr. Farber's analysis does not address the issue of variation in statistical outcomes for individual women or subsets of women over the class period. His aggregated statistical findings therefore do not specifically relate to the question which the user of his analyses will have to address: from a statistical perspective, the issues are whether the claims of female employees at Microsoft are amenable to common treatment, and whether the statistical outcomes are traceable to specific common and adverse pay or promotion policies.

21. Dr. Farber uses multiple regression techniques to study pay differences between women and men. These methods allows an analyst to hold constant the characteristics that affect pay for all employees and measure the pay difference that remains between women and men and that in the absence of other non-gender factors might be attributable to gender. The result of such an analysis is a "regression coefficient" on the variable in the model that identifies female status – this is the measure of the quantitative magnitude of the difference between male and female pay. However, for this measure to be meaningful regarding the measured difference in pay by gender the model cannot omit factors that both affect pay, and systematically differ by gender. If factors which influence pay are left out of the model, and those factors are correlated to female status, then the measured pay difference will be overstated because some of the effect of that omitted variable will be essentially added, or impounded into the gender coefficient. In other words, the regression coefficient on gender does not measure discrimination per se. What is important to

understand is that an *inference of discrimination* is based on the residual differences measured by a gender variable, once other factors that impact pay are taken into account. This is because "discrimination" is not based on an observable factor in data – it is an inferred conclusion. I will address this at length elsewhere in the report. What I want to highlight here is that the gender regression coefficient represents the *average* difference in pay between women and men, taking into account their characteristics as measured by what the analyst chooses to include in the statistical model.

22. All real world phenomena can be described by a central tendency, or average, and a variance, or dispersion around the average.[12] When there is not much underlying variation in the data and associated analytical outcomes then an average is potentially a useful summary measure. If there is a lot of variation in pay, both in the ranges of pay levels across and within job categories as well as in the individual statistical outcomes, an average can be misleading. As a simple example in a descriptive statistics context, imagine a group of 100 employees whose average earning are $150,000. Assume they are a random sample of a larger population. If all of these sampled employees earn between $145,000 and $155,000, then the average is a good summary measure of income in that sample and the extrapolated difference, or "error" between that average and any individual's actual pay in the larger population is relatively small. Now imagine instead that half of the employees earn $75,000 a year and half earn $225,000. Average earnings are still $150,000 but as a summary measure, the average does not capture "typical" earnings very well and this single number obscures the fact that there are two distinctly different earnings groups in the wider population. The reason this matters is that in the low variation case, there are unlikely to be systematic or even idiosyncratic issues that would have to be explored to

[12] There are various other descriptive measures, but these are the fundamental measures analysts examine when characterizing a phenomenon.

understand what the larger employee population was all about. Pay falls in a narrow range, and since it does, one can be confident that is also the case in the larger population. No further fact gathering would be useful. However, if a group of individuals has average earnings of $150,000, but earnings can range from $75,000 to $225,000, clearly something meaningful must differ between these sub groups, and simply applying the average to the larger population would tell you little or nothing about who among these non-studied people earned $75,000, who earned $225,000, and more importantly, why. They might occupy two very different jobs, or work in two different companies plus have different jobs, etc. One would have to identify these facts in order to properly understand the characteristics of this higher variance population. As we shall see, this is the problem with Dr. Farber's sole focus on the average: There are substantial and meaningful unexplained differences in statistical outcomes for putative class members that beg the question as to why. Thus one cannot conclude from Dr. Farber's statistical analysis if there is some common set of forces at work, or if there are many different forces, some working to the apparent statistical benefit of women, and some not.

Dr. Farber's aggregated pay regressions contain much underlying variation in individual female employee outcomes and when examined by decision maker, show wide variations in the outcomes of women under different supervisors/decision makers.

23. Dr. Farber estimates five pay regressions and reports the gender coefficient from each model in Table 3 of his report. Elsewhere in my report, I discuss the deficiencies with each model, but in this section, I take his models at face value and simply focus on the variations underlying his aggregated results. I will concentrate on the last model he estimates, "Model 5" in Table 3, taking it at face value and as estimated on the data he used. This model estimates the average difference between women and men holding constant year, age (and age squared to

account for a non-linear effect on pay), tenure at Microsoft (and tenure squared), the state and city in which the employee works, their pay scale type, performance rating, discipline and Standard Title. His data includes the years 2010 through 2016.[13] This model estimates that the average overall gender pay difference is 2.8% (as shown in Table 3 of his report).

24. As noted, a regression model essentially predicts *on average* what someone with particular characteristics should earn. A gender coefficient of -2.8% means that on average, women's predicted pay is 2.8% lower than a man with roughly similar characteristics.[14] One of the characteristics in Dr. Farber's model is years of Microsoft tenure. A coefficient of 0.6% on years of tenure means that pay is increased 0.6% for each year a person worked at Microsoft, all else equal.[15] Using the regression model coefficients and a person's actual characteristics, the regression can be used to predict or "fit" pay for each individual employee in the data analyzed. It is then possible to compare each employee's actual pay to this fitted, predicted pay. It is also possible to test whether the difference between actual pay and predicted pay is statistically significant for each individual.

25. I re-run Dr. Farber's model, but I drop gender as a control variable so that predicted pay does not systematically separate men and women but instead models the impact their other non-gender characteristics have on pay. When actual and expected pay are compared for the women in Dr. Farber's analysis, there are women in the data whose actual pay exceeds what the model predicts based on their non-gender job-related characteristics and other women who earn less than the model predicts based on their non-gender characteristics. An average pay difference of

[13] The class period starts in 2012, but for purposes of this section, I take his results as is. Following his example, I adopt the FY2011-FY2016 data structure. In other words, September 2012 through August 2013 is FY2013.
[14] Where those characteristics are measured at their respective means.
[15] Abstracting for purposes of the illustration from the squared term.

2.8% cannot tell us is whether most women are paid less than predicted or if there is considerable variability in their actual relative to their predicted pay.[16]

26. The variability in the data is made evident by the graph below for women in 2015. I graph 2015 as an example, though the model is estimated over all years.[17] The graph plots actual pay for each employee on the vertical axis and what their expected pay would be based on factors other than gender on the horizontal axis. The predicted values range along the horizontal axis between about [redacted]. Actual pay ranges on the vertical axis from about [redacted], a range much wider than the model can account for. The solid black line indicates where actual pay equals predicted pay. Dots above the black line indicate women who are paid above what the model predicts; dots below the line indicate women who are paid less than the model predicts.

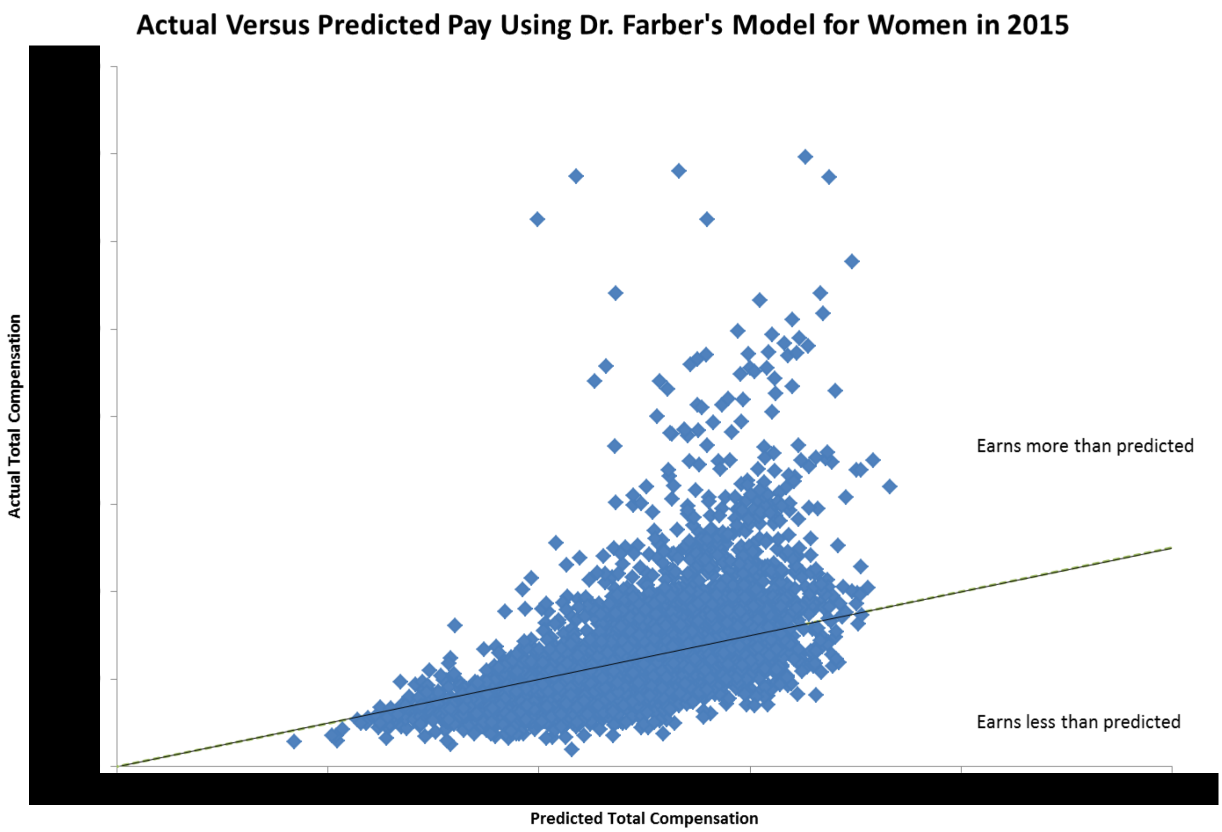
27. For example, take the point along the horizontal axis at [redacted] which is where predicted pay equals [redacted] If one were to draw a straight line vertically from that point upwards toward the title of the graph, and the line intersected with a dot for an employee below the black line, that would indicate someone who was paid below their predicted pay level of [redacted] If one were to continue that same line up from [redacted] and intersect it with an employee dot above the black line, that is someone whose actual pay is higher than the predicted [redacted] Both of those dots represent women, who based on their observable characteristics

[16] One might argue that of course there will be dispersion in predicted values relative to actual values in any regression analysis. However, it is important to examine the extent to which these values depart from one another. It is also my understanding that it can be important in a class certification context to note that substantial numbers of women have actual pay in excess of what is expected, based on the model.

[17] I have chosen to present 2015 for illustrative purposes, but the results of what I present for 2015 are essentially similar in the other years where I am able to apply the various approaches I use in this section. Note that the model used is Dr. Farber's all years model, and I have simply used the data for 2015 for purposes of the charting exercise. Dr. Farber controls for year in his overall model, and thus one of the characteristics applied to all employees for purposes of computing their expected pay in 2015 would be Dr. Farber's 2015 indicator variable.

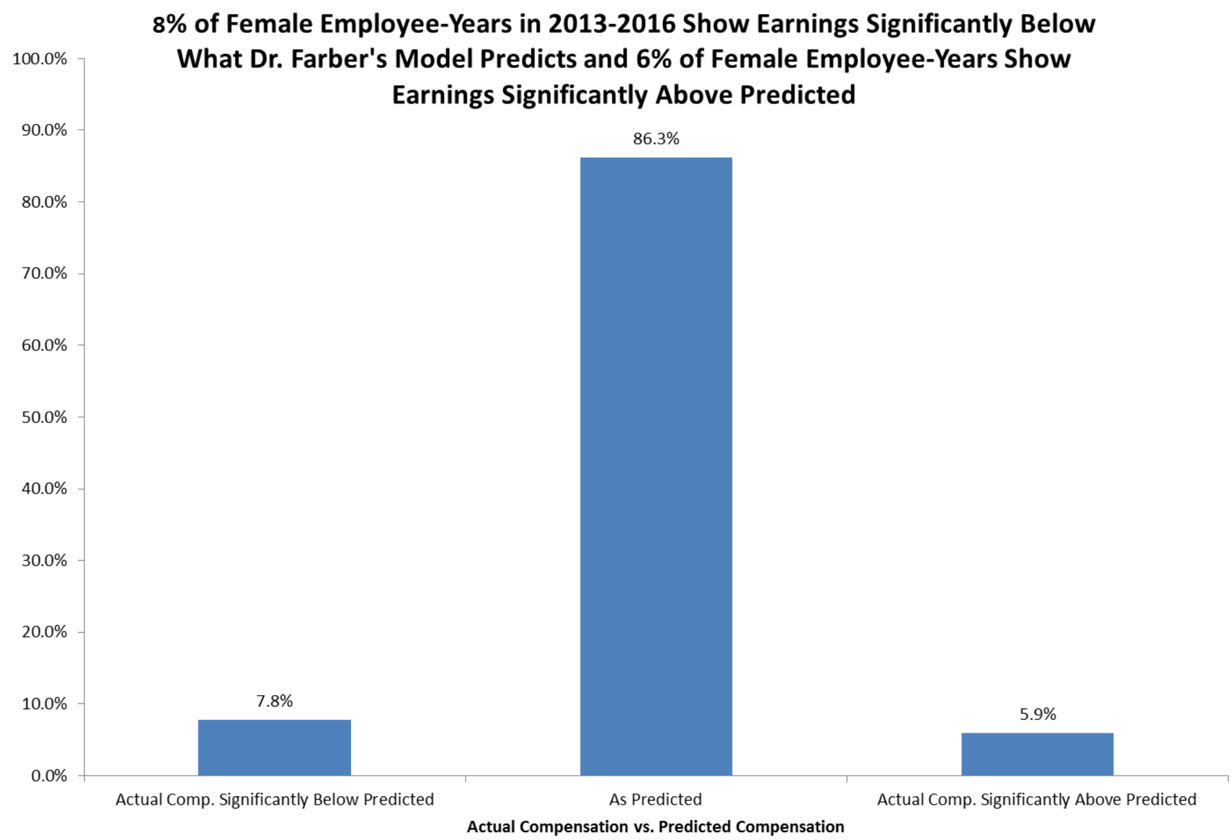
were *both* predicted to be paid [redacted], but one woman is paid more than the expected [redacted] and the other woman is paid less. This difference in actual pay between two observationally similar employees is unexplained by the regression model, because the model makes the same pay prediction for both employees. Note that in this graph, only women are charted, and thus whatever is causing their pay to differ, it is not gender.

28. There are a considerable number of women who earn more than Dr. Farber's model predicts, with no corrections to its flaws - about 33.7% of the women in his data for 2015. I can also examine women whose actual pay is statistically significantly different than predicted by the regression model based on their characteristics. I find that 6.2% of women in his data for 2015 earn statistically significantly less than predicted by his model, and 5.9% of the women in his data that year earn statistically significantly more than predicted by his model.



Note: Dr. Farber's Model 5 with no gender control is used to calculate predicted pay.

29. This same categorization can be calculated over all the data, not just 2015. The results are similar. Because Dr. Farber estimates his model using all years, each observation is an employee-year; for example, a woman who worked for three years in the class period would appear in the data three times. I find, using his data and model, that only 7.8% of observations in his data indicate a woman who earned statistically significantly less than predicted that year. Another 5.9% earned statistically significantly more than his model predicted. This speaks to the aggregated nature of his analysis. By aggregating all women together to gauge statistical significance overall Dr. Farber obtains statistically significant results on an overall basis. However, an issue at class certification is whether the aggregated measured impact is "common." As presented, Dr. Farber's results do not indicate that.



<u>Dr. Farber's pay models do not account for the decision makers in the review, pay and promotion process, but his results can be summarized by decision maker</u>

30. Another factor Dr. Farber does not take into account is variation among supervisors and the decisions that can be associated with them. It is my understanding that performance evaluation decisions are made by employee managers at a local level, and that these then feed into pay and promotion decisions. Again, a single regression coefficient obscures the fact that a single decision maker is not at work in pay and promotion decisions: employee performance, pay and promotion outcomes depend on many individual managers' decisions. I can graph the same pay data discussed above subset by supervisor, to study whether outcomes also vary by decision-maker.

31. My understanding of the process is that employees are evaluated for job performance by their direct manager and then those reviews are grouped together and the reviews are "calibrated" through group discussions. The process is then repeated at higher levels until they are approved and finalized.[18] The promotion nomination and approval moves up the hierarchy of managers during this process and is finalized by an approving leader or calibration owner.[19] Certain components of pay are then awarded based on Stock Level, current pay, and performance rating.

32. I received monthly snapshot data that indicate for every employee their direct supervisor, that person's direct supervisor, and so on up through the hierarchy for September 2014 on. Before then, the snapshots exist on an annual basis for 2013 and organization charts containing similar information exist for 2012. I can use this information for 2015 to show how the single regression coefficient from Dr. Farber's highly aggregated pay model does not imply a common

[18] Deposition of John Adrian Ritchie Volume II on June 30, 2016 p. 517:1-4, p. 517:16-17.
[19] Deposition of Larissa Johnson on May 12, 2016 p. 51:15-21 and Ritchie Exhibit 44 MSFT_MOUSSOURIS_00004283.

adverse impact on women -- even if they share a supervisor, their outcomes can vary dramatically.[20]

33. I examine supervisor impact at varying levels. Level 2 supervisors can supervise anywhere from 1 to almost 3,000 technical employees in the data I have[21] and most have a Stock Level between 70 and 83. Level 3 supervisors can supervise anywhere from 1 to 1,065 employees in the data, and tend to fall in Stock Levels 67 to 80. Level 4 supervisors tend to be in Stock Levels 65 to 70, and supervise from 1 to over 600 employees in the data.

34. Note that supervisors are not used as controls in Dr. Farber's statistical models – and I have not run Dr. Farber's models separately by supervisor for this exercise. Rather, the differences between actual and predicted pay, and the determination of whether that difference is statistically significant, come straight from Dr. Farber's aggregated model, minus gender.[22] What I have done here is to gather and examine the results from his aggregated model for each supervisor. In the analyses below, I restrict the graphs to supervisors of at least 10 employees for convenience, but again, there is no issue with small sample sizes: the power of the statistical tests depends on the aggregated model and data, not the number of employees a supervisor manages. For the Level 2 analyses, 99.9% of female employees are included under this restriction in the graph, meaning that almost all work for supervisors of 10 or more employees. For Level 3,

[20] Appendix 1 contains the analysis for 2016 (pages 9-14). Comparable supervisor hierarchy data is not available for 2013 and 2014. Pay variability charts for 2013 and 2014 are excluded from this analysis due to gaps in the supervisory snapshot data and other unavailable information during this period. While the supervisory data spans 8/2012 to 6/2016, monthly snapshots are missing from 9/2012 to 8/2013, and from 10/2013 to 5/2014. Therefore, 60% of newly hired employees in 2013 and 2014 do not have supervisory information; thus, the missing hierarchy information causes employees to be missing in non-random ways in the pay analyses. In the promotion models, the missing supervisor data is not an issue because new hires are not typically evaluated for promotion, and thus they have little weight in a promotion analysis.

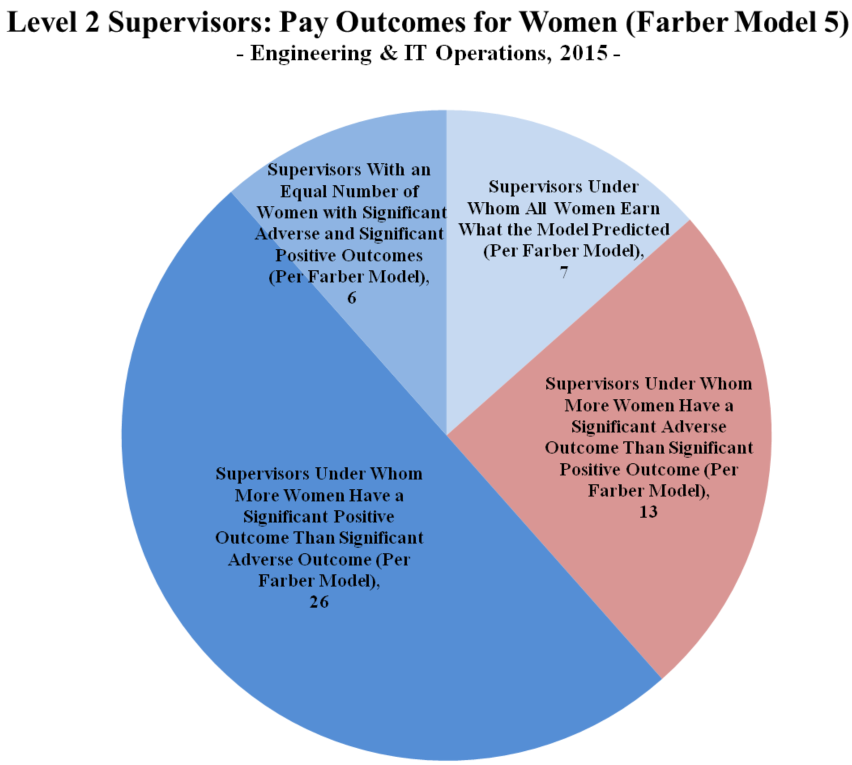
[21] They may also supervise non-technical employees, but those employees are not present in my data.

[22] Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance rating, Discipline, and Standard Title, in addition to gender. Here, I simply drop gender from his model.

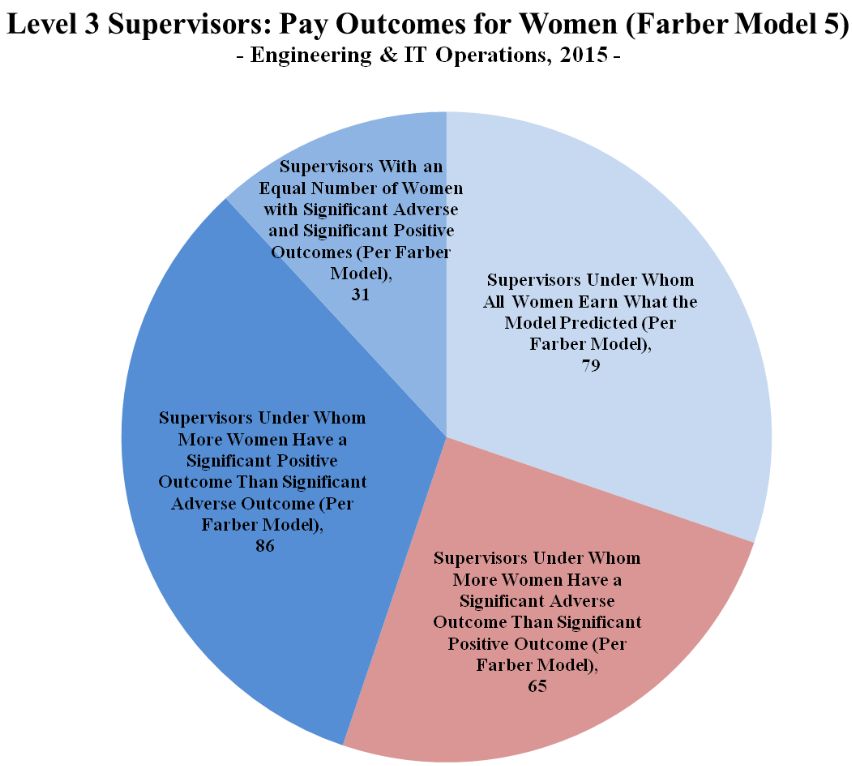
98.2% of female employees are included, and for Level 4, 83.0% of female employees are covered by the analysis.

35. The results show that there are supervisors under whom all women earn about what Dr. Farber's model predicts (i.e., the difference between actual pay and the pay predicted by his aggregated model is not statistically significant). This is shown in the light blue slice of the pie chart below for Level 2 supervisors in 2015. The somewhat darker blue indicates supervisors under whom there are equal numbers of women who earn significantly more than predicted and earn significantly less than predicted. The darkest blue slice represents supervisors under whom there are more women earning significantly above the model's prediction than there are earning significantly below predicted. The red slice indicates the share of supervisors under whom more women earn significantly less than predicted than earn significantly more. These results are generated using Dr. Farber's model with its flaws included, but even so, it is apparent that the Level 2 supervisors with more negative than positive results for women are in the minority.[23] The same exercise can be conducted for Level 3 and 4 supervisors in 2015.

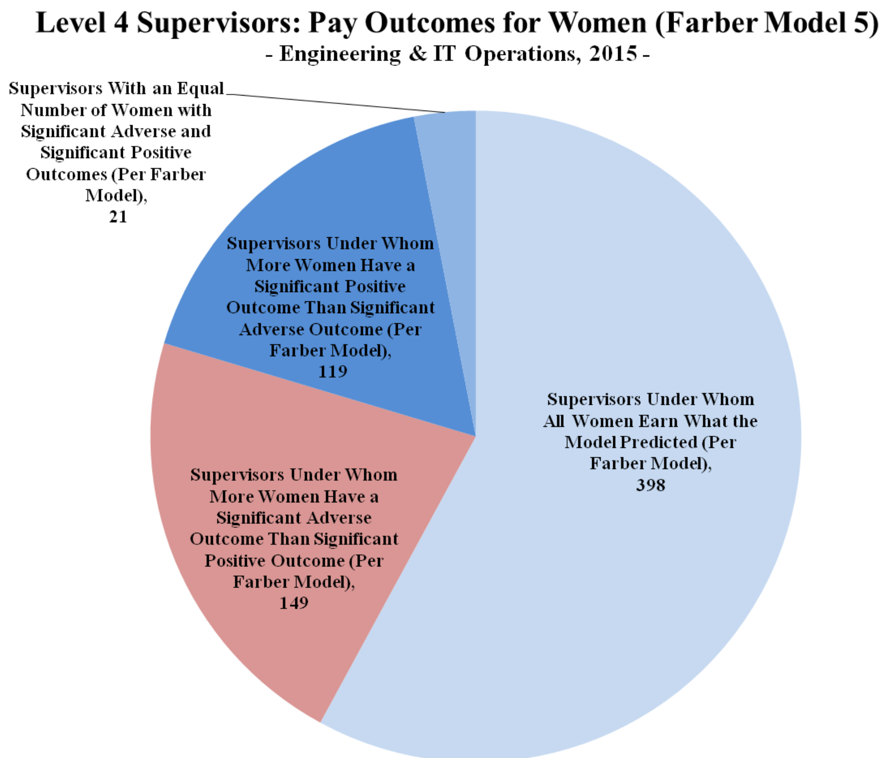
[23] Most women (69.2%) are also in the categories colored blue, and 30.8% work for supervisors in the red category.



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 2 supervisors with at least 10 employees and accounts for 99% of female employees.



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 3 supervisors with at least 10 employees and accounts for 98% of female employees.



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 4 supervisors with at least 10 employees and accounts for 83% of female employees.

36. The charts show that supervisors under whom more women earn significantly less as opposed to earning significantly more according to Dr. Farber's model prediction are in the minority.[24] To reiterate, these predictions and significance levels are generated using Dr. Farber's flawed model, but serve to show that despite his regression coefficient showing a 2.8% pay difference between men and women, there is actually quite a bit of underlying variation.

37. The charts show that, using Dr. Farber's model and his data, any given supervisor could oversee women who earn more than predicted, less than predicted, about what the model predicts, or a mix – meaning that some women in their reporting structure earn more than predicted and others in that same reporting structure earn less than predicted. As noted above,

[24] Using the Level 3 supervisors, 56.6% of women are in the blue categories. Under Level 4 supervisors, 61.8% of women are in the blue categories.

these are variations found within Dr. Farber's models, not my own aggregated models, which will be discussed in detail later in this report.

38. Dr. Farber does not study the variation in outcomes by supervisors, who make the pay and promotion decisions at issue in this case. Most women work under supervisors whose pay decisions may result in all three of the following types of outcomes: significantly higher pay than predicted, significantly lower, or about what the model predicts. In other words, since the outcomes are not consistently in one direction or the other, it is inconsistent to claim that gender is a determinative factor in that particular supervisor's decisions.

Outcomes based on actual pay compared to pay as predicted by Dr. Farber's model vary among the Named Plaintiffs and Plaintiffs' declarants

39. I examined what Dr. Farber's pay Model 5 implied for the two Named Plaintiffs and nine Plaintiffs' declarants. Applying Dr. Farber's model to them individually, neither Named Plaintiff was paid statistically significantly below what Dr. Farber's Model 5 predicts. Indeed, Ms. Moussouris was paid more than predicted, as were six of the nine other declarants. Of the four whose earnings were below predicted (including Ms. Muenchow), none were statistically significant.

40. The blue bars in the chart below show actual pay by year for Ms. Muenchow and Ms. Moussouris. The red bars show the earnings that the model predicts based on their non-gender characteristics. The studentized residual is indicated above each year's pair of actual and expected earnings.[25] A studentized residual can be used as a statistical test of whether the difference between the red and blue bar is statistically significant: if the test statistic is larger

[25] A studentized residual is a standard deviation measure of the difference between actual and predicted pay for an individual observation in a regression model. The units are in standard deviations. For example, a studentized residual of -1.5 would mean that there is a 1.5 standard deviations difference between actual and expected pay for the employee in question, with actual pay being below predicted pay.

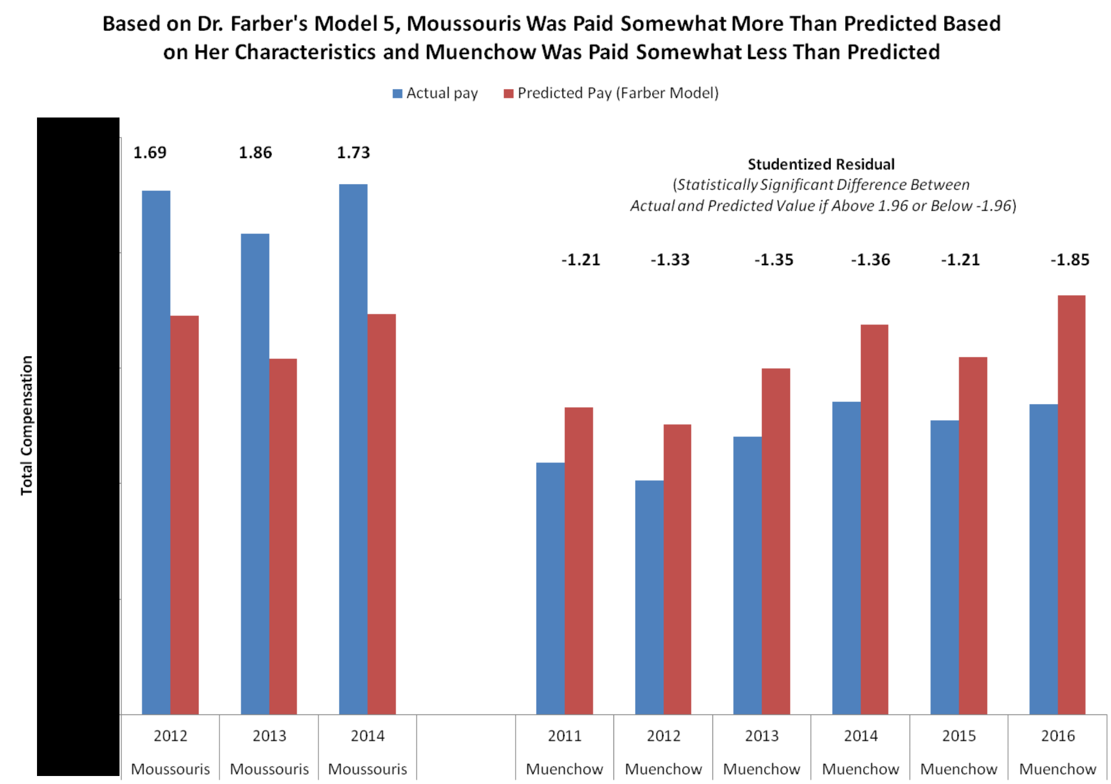
than 1.96 or smaller than -1.96, then the difference is statistically significant; if it is between -1.96 and +1.96, then the difference is not statistically significant. The chart shows that Ms. Muenchow earned less than the model predicts, but that the difference is never statistically significant. Ms. Moussouris consistently earned more than predicted, though again the difference is not statistically significant.

41. Indeed, in FY 2012, 2013, and 2014, Ms. Moussouris has the highest annual salary in her cost center.[26] In each of these years, she receives a higher performance rating than her direct supervisors at the time ([redacted] in 2012 and 2013, [redacted] in 2014).[27] She is among the highest-rated people on her team as well. Furthermore, in FY 2012 and 2014, Moussouris has the highest total compensation in her cost center, and is paid more than her supervisors.

42. FY 2013 is the only year Plaintiff Moussouris's total compensation is not the highest in the group. In that year, [redacted] is re-hired and [redacted] his total compensation to [redacted] higher than Moussouris ([redacted]). Their total compensation is extremely close in spite of the fact that [redacted]. Moreover, the following fiscal year, Plaintiff Moussouris returns to being the highest-compensated in her cost center ([redacted]), even though [redacted] is her direct supervisor and has [redacted].

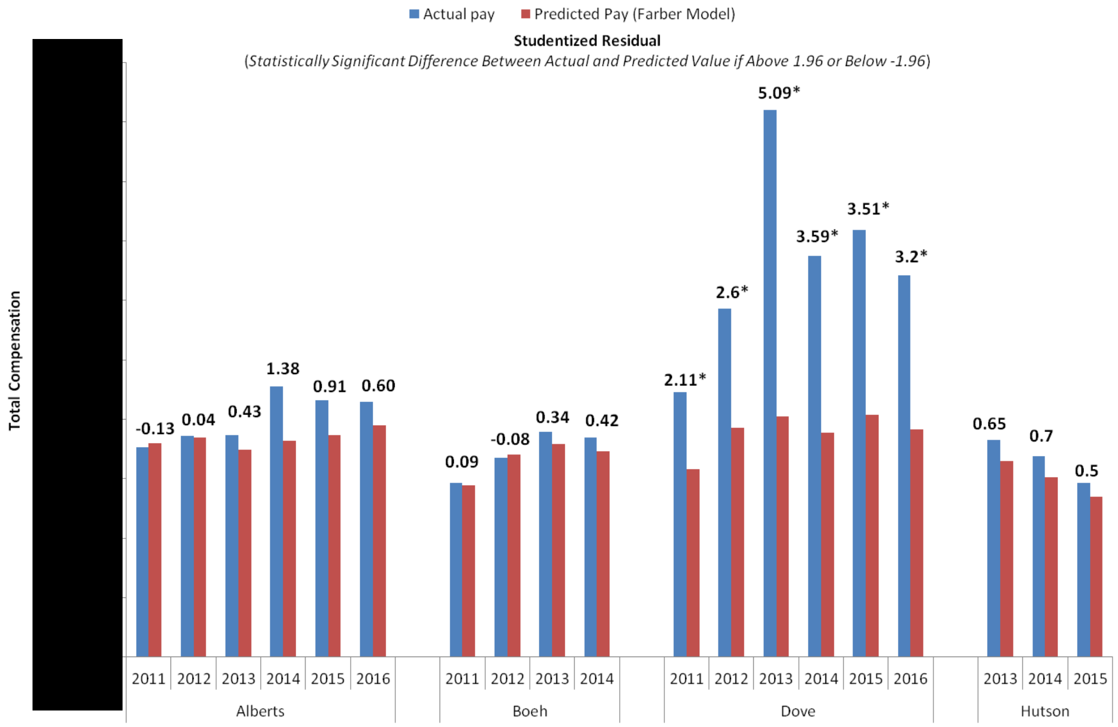
[26] In Ms. Moussouris' Response to First Set of Interrogatories on May 3, 2016, she list four comparators. None appear to be relevant comparators. [redacted] was promoted from Stock Level 64 to Stock Level 65 in March of 2011, before the class period. [redacted] was promoted to Stock Level 65 in September 2014, after Ms. Moussouris had left Microsoft (May 2014). Throughout the period she was employed, he worked in a different organization than she did (his organization was "Finance, HR & Legal," whereas hers was "Engineering"). [redacted] was promoted from level 64 to level 65 in September 2012, meaning he starts the class period in level 65. [redacted] was not promoted to level 65 until March 2015 (not 2013, as Ms. Moussouris stated), well after she had left Microsoft. In 2013, he had been promoted from level 63 to level 64 (at which point she was already at level 64).

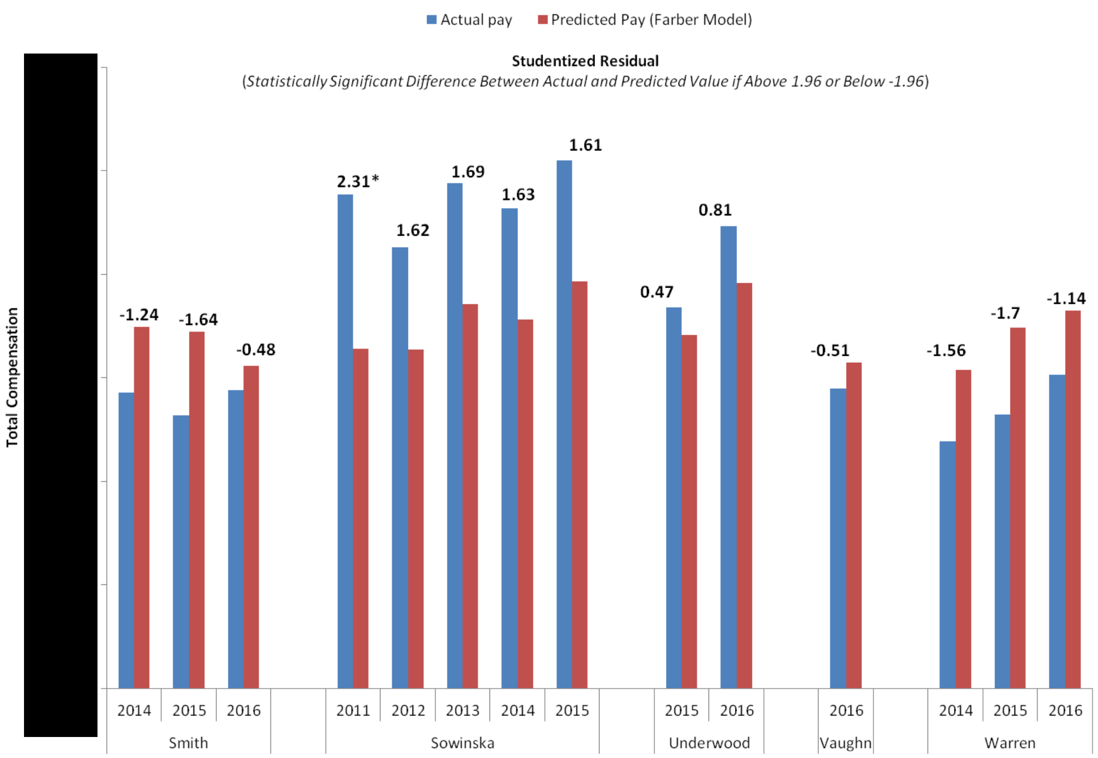
[27] Salary figures, tenure and performance ratings are taken from Dr. Farber's data.



43. There are also nine women who submitted declarations in support for Plaintiffs' motion for class certification. The same comparison of their actual and expected earnings shows that six of the nine earned more than predicted by Dr. Farber's Model 5, and that Ms. Dove earned statistically significantly more than predicted in every year as did Ms. Sowinska in one year. Of the three who earned less than predicted, the difference was never statistically significant.

Based on Dr. Farber's Model 5, Six Out of Nine Declarants Were Paid More Than Predicted
- Actual and Predicted Pay for the Declarants Using Dr. Farber's Model 5 -





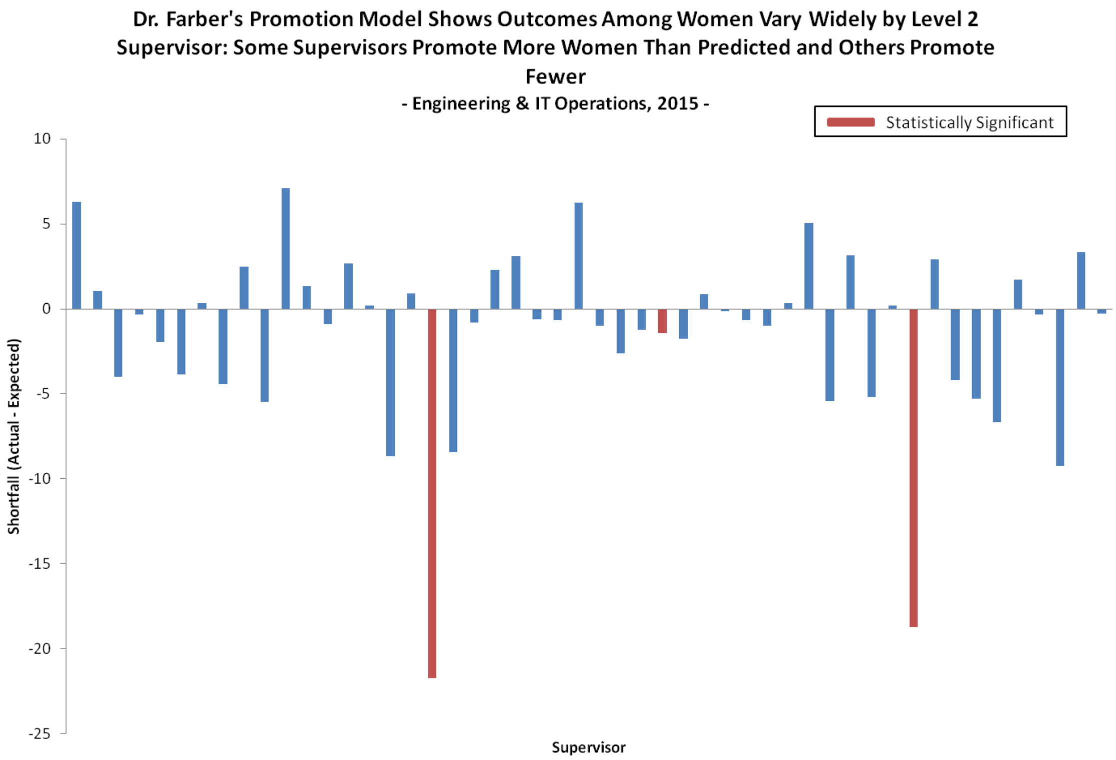
<u>Promotion outcomes by supervisor exhibit the same variation as seen in the pay analysis</u>

44. Using Dr. Farber's models, promotion outcomes vary widely among women even when they share a supervisor. The probit model used by Dr. Farber did not take the decision makers in the performance rating, pay and promotion process into account. However, his model generates predicted probabilities of promotion that can then be compared to actual promotions to gauge whether there is a shortfall for women relative to the expected number of promotions. In his report, he uses men-only models to generate predicted probabilities for promotion. I follow his example in my replications of his promotion analyses.

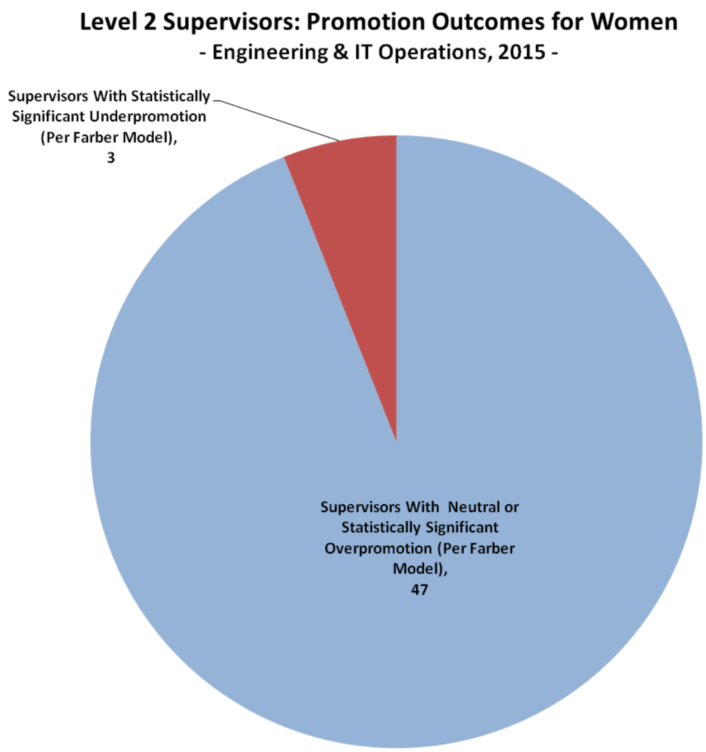
45. Note again that supervisors are <u>not</u> used as controls in the aggregated model – these are not statistical models that have been modeled separately by supervisor. Rather, the differences between actual and predicted promotions, as well as the statistical significance calculations, come straight from Dr. Farber's aggregated model. The power of the statistical tests depends on the aggregated model and data, not the number of employees a supervisor manages. All I have done is plot the results from his model sorted and grouped by supervisor after running his aggregated models.

46. The bar chart below shows that according to Dr. Farber's model, 20 Level 2 supervisors promoted more women than expected in 2015. The pie chart shows that even according to his model, 94% of supervisors promote women in an expected amount or at levels significantly above expected. Similar graphs for Level 3 and Level 4 supervisors indicate much the same: under most supervisors, women are promoted at or above the expected rate.[28]

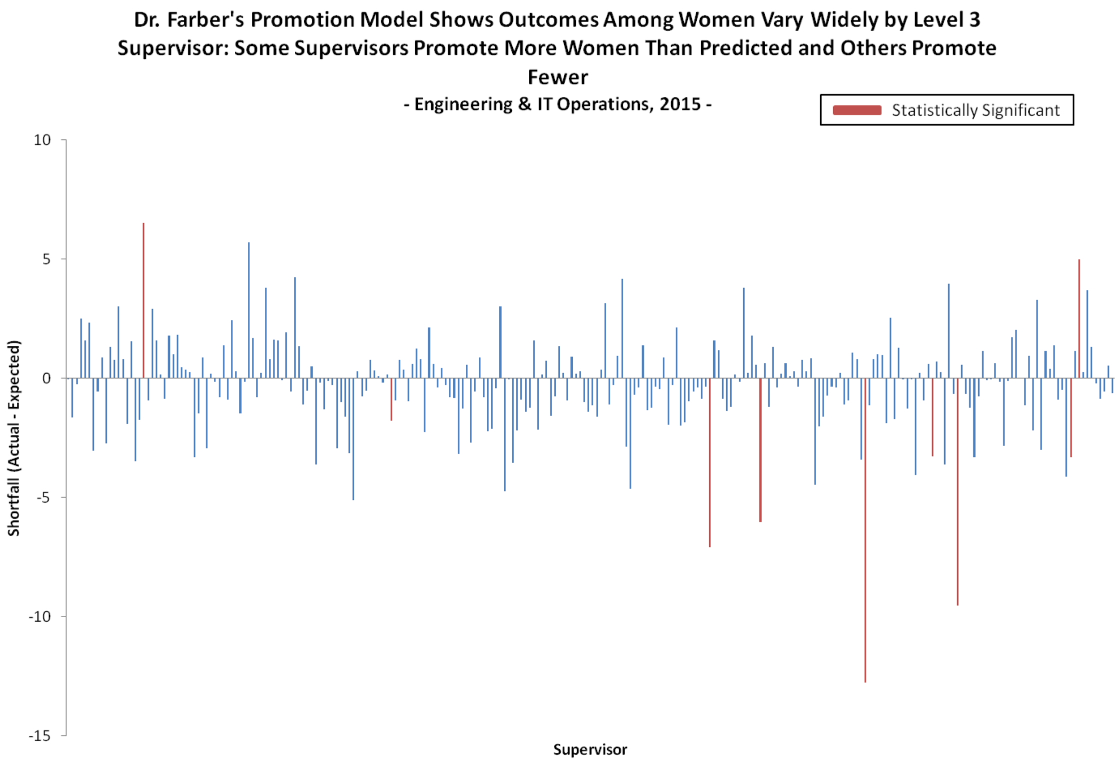
[28] Appendix 1 contains the same charts for all years (pages 15-32).



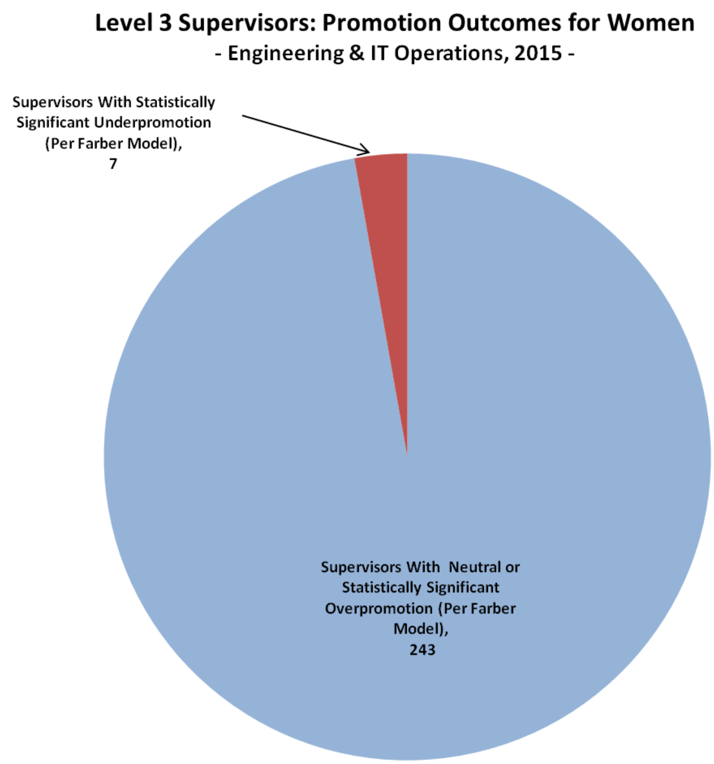
Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 2 supervisors with at least 10 employees and accounts for 99% of female employees.



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 2 supervisors with at least 10 employees and accounts for 99% of female employees.



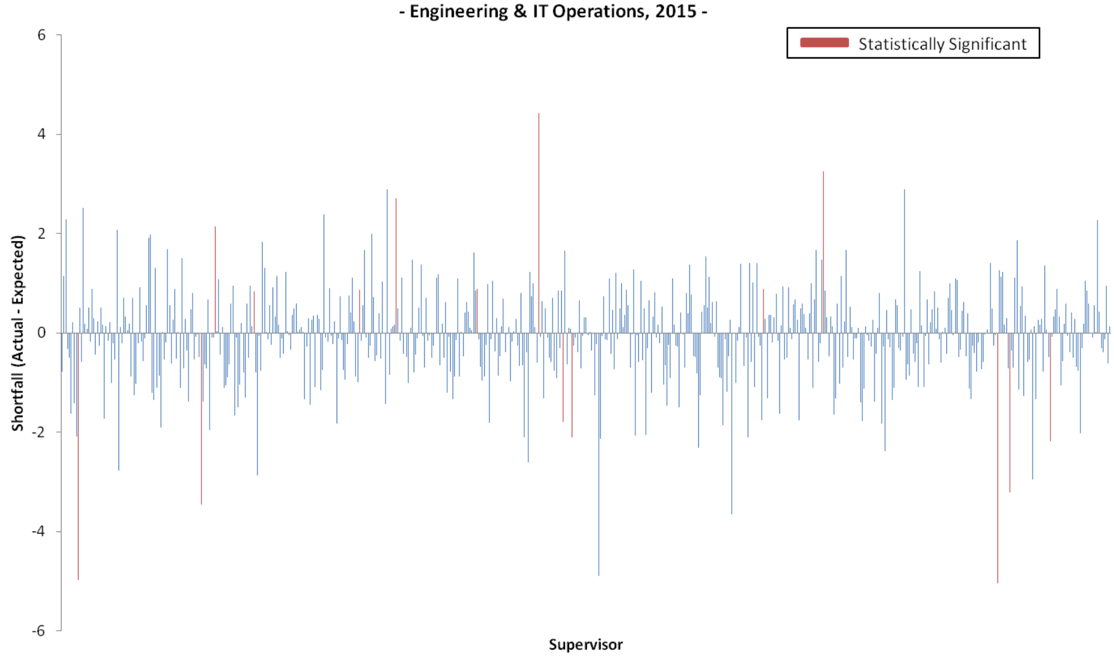
Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 3 supervisors with at least 10 employees and accounts for 97% of female employees.



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 3 supervisors with at least 10 employees and accounts for 97% of female employees.

Dr. Farber's Promotion Model Shows Outcomes Among Women Vary Widely by Level 4 Supervisor: Some Supervisors Promote More Women Than Predicted and Others Promote Fewer

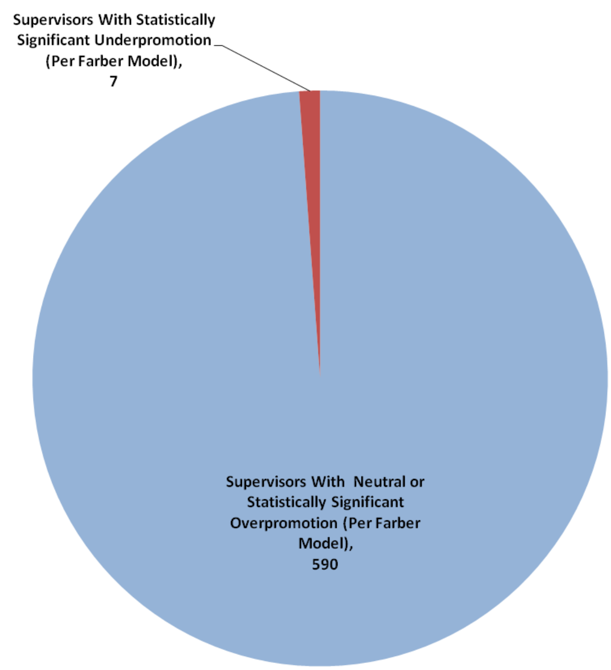
- Engineering & IT Operations, 2015 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 4 supervisors with at least 10 employees and accounts for 78% of female employees.

Level 4 Supervisors: Promotion Outcomes for Women

- Engineering & IT Operations, 2015 -

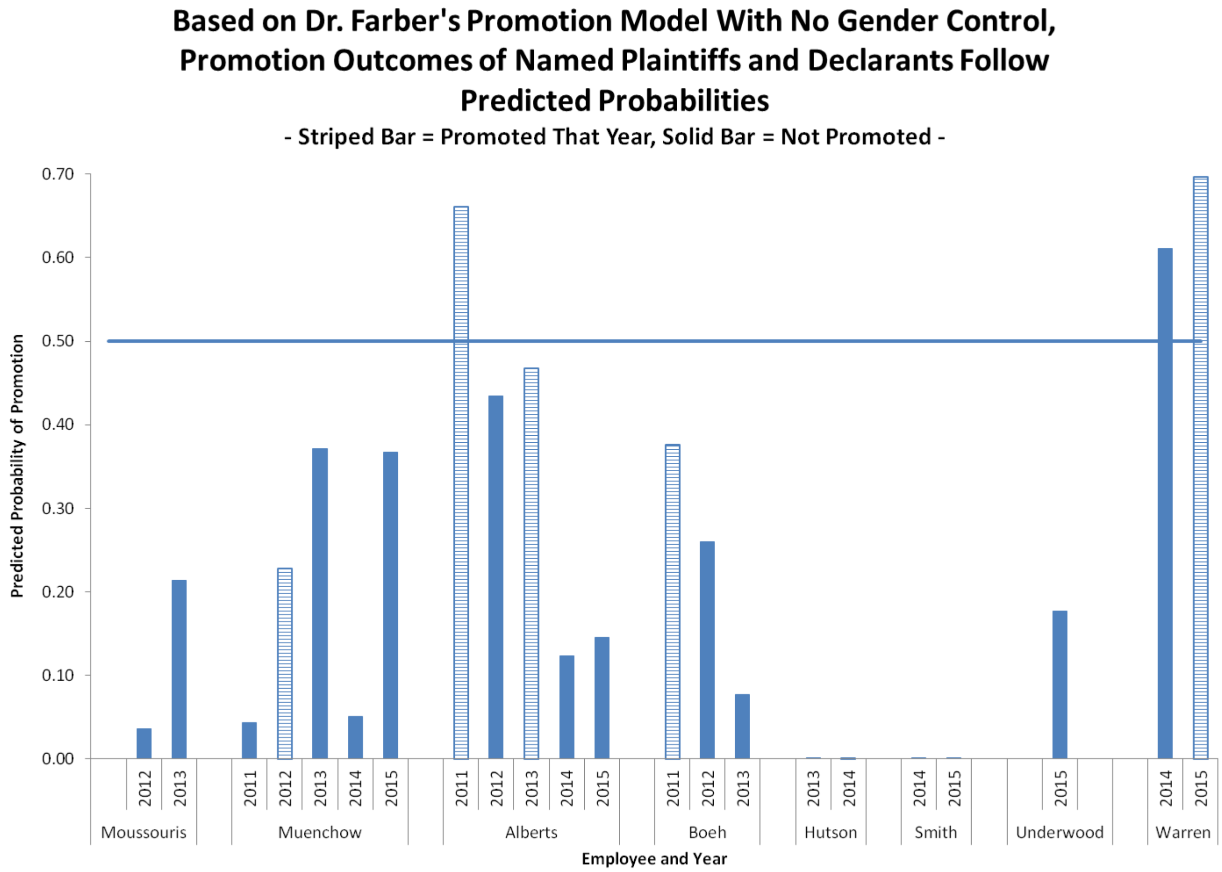


Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 4 supervisors with at least 10 employees and accounts for 78% of female employees.

Dr. Farber's promotion model predicts fewer promotions among the Named Plaintiffs and Plaintiffs' declarants than actually occurred

47. A similar exercise for the Named Plaintiffs and individual declarants can be performed using Dr. Farber's promotion model that underlies Tables 6 and 7 in his report. The model predicts the probability of promotion each year. I used his model, minus gender, and his data to generate the predicted probability of promotion for each person. As with the pay regressions, I include both men and women in the model but do not control for gender, in order to base the predictions on their characteristics other than gender.

48. Dr. Farber's model predicts that Moussouris had a 3.7% chance of promotion between 2012 and 2013. When I examine the job history file, I see that she was not promoted. In 2013, her predicted probability of promotion was 21.4% based on Dr. Farber's model. According to the job history data, she was not promoted between 2013 and 2014. The model cannot estimate a probability between 2014 and 2015 because Ms. Moussouris left Microsoft in the interim. In the graph below, I show predicted probabilities taken from Dr. Farber's model for each of the Named Plaintiffs and Plaintiffs' declarants (the height of the bar). Solid bars indicate the person was not promoted that year, and striped bars indicate a promotion.



49. If we assume that a probability above 50% indicates a promotion is more likely than not to occur, then Dr. Farber's model predicted three promotions should have occurred. In fact, five promotions occurred.[29] Only once does his model predict that a promotion should have occurred when it did not. For that declarant, Warren, a promotion did occur the following year.

__The varieties of Microsoft experience within the putative class in terms of their employment circumstances are considerable__

50. There are hundreds of different jobs in dozens of work settings. Total compensation in Dr. Farber's dataset ranges from about [redacted]. But as shown in some detail

[29] The model cannot be estimated for Ms. Sowinska or Ms. Dove because they were level 65 and Dr. Farber's promotion model only examines promotions through level 64. Ms. Vaughn drops out of the analysis because she does not have two adjacent years worked during the class period.

above, there are also wide variations in the statistical outcomes within the aggregated analyses Dr. Farber performs. If one examines individual employee statistically predicted pay versus their actual pay, large unexplained differences are found. This variability remains even when examining outcomes for women who share a supervisor, who makes decisions about performance ratings, pay and promotion. Looking at promotions by supervisor, some supervisors appear to "over-promote" women and some appear to under-promote women. There is a wide range of varying outcomes under the hood of Dr. Farber's aggregated analyses.

51. I turn next to responding to Dr. Farber's analysis of performance ratings, promotion and pay.

ANALYSIS OF PERFORMANCE EVALUATION

52. Dr. Farber analyzes average performance ratings by year and concludes that there is no gender gap in performance ratings during the class period. The only statistically significant difference in ratings he finds, which was very small, occurred prior to the class period. Had he disaggregated the data by year for the class period, he would have found a small but statistically significant difference in ratings in 2013, amounting to 0.03 points. This difference is tiny and has no practical significance whatsoever, and is unlikely to have had even a measureable impact on either pay or promotions. The chart below shows the year by year results, as well as the percentage of female ratings relative to male ratings.

Analysis of Average Gender Difference in Performance Metrics
- 2013 – 2016 -

	Average Rating Male	Average Rating Female	Female Avg as Pct of Male Avg	Significance	Employee Years
	[1]	[2]	[3]	[4]	[5]
Performance Rating					
2013	3.43	3.40	99.1%	*	[redacted]
2014	3.45	3.44	99.7%		[redacted]
Reward Outcome					
2015	4.69	4.69	100.0%		[redacted]
2016	4.71	4.72	100.2%		[redacted]

<u>There is no difference between men and women on average in performance ratings, in contrast to Plaintiffs' theory of the case</u>

53. As discussed below, Dr. Farber's pay models demonstrate that the small differences in the performance ratings over even the pre-class years do not explain <u>any</u> of the pay difference between men and women in his pay analyses. This is evident because when he included performance ratings in his pay models, the difference in pay between men and women did not change. And yet the Second Amended Complaint argues that women are rated lower than men and that this drives pay and promotion differences.[30] Presumably because Dr. Farber's statistical results show no differences in ratings during the class period, Plaintiffs' Motion for Class Certification adjusts their hypothesis to a theory that somehow ratings and pay and promotions are separate and independent processes. Yet the overall explanatory power of the Farber pay regressions increases substantially once ratings are added. Ratings are indeed an important

[30] Second Amended Complaint, ¶43: "Microsoft determines employees' compensation primarily by their performance review results. Because female technical employees systematically receive worse results, they also earn less than their male peers."

factor in explaining compensation for all employees, male and female alike, but Dr. Farber's results show that women and men are treated equally in that process.

Some components of pay can be shown to rely directly on performance ratings

54. Stock awards, reward bonuses and merit increases in base pay explicitly rely on the performance rating. The table below presents regression results relating these compensation components to performance ratings to examine whether they are determined in the ways indicated, which are: [redacted][31] [redacted][32] [redacted][33]

55. The table below presents the results for regressions of dollars awarded in stock on year and Stock Level, excluding performance measures.[34] Those two factors explain 84.5% of the variation in dollars awarded. Adding performance ratings shows that 99.4% of the variation in dollars awarded is explained by year, Stock Level and performance rating. There is virtually no unexplained variation, based on the R-squared figure being almost equal to one.[35] If you know

[31] Declaration of Larissa Johnson, p.4. See also MSFT_MOUSSOURIS_00308259.
[32] Declaration of Shreetjit Sugathan, p.5. See also MSFT_MOUSSOURIS_00308259.
[33] Declaration of Shreetjit Sugathan, p.5. See also MSFT_MOUSSOURIS_00308259.
[34] In the analysis, the assigned stock level is employee's level as of August 31, before annual review promotions are effective. Performance is measured as the performance rating effective as of September 1. Bonus Eligible Salary (BES) is the actual amount of base pay earned by employee over the fiscal year, adjusted for any leaves of absences or changes in salary. Merit Percent is the employee's base salary percentage increase from the merit award amount.
[35] R-squared ranges from zero to 1, and represents the proportion (or percentage when multiplied by 100) of the variation in the dependent variable being studied that can be explained by the independent variables included in the regression model.

an employee's Stock Level and performance rating, you essentially know what their stock value reward bonus was. Note that adding an indicator for female does not increase the explanatory power of the model, nor is gender a statistically significant predictor of stock awards. There is only a $23 difference between women and men in this pay component and that tiny difference is not statistically significant, let alone practically significant.

Annual Review Cycle Stock Rewards (Dollars) Rely on Performance Ratings

- 2013-2016 -

Model	Controls	Adjusted R^2	Employee Years	Female Coefficient	T-Stat
	[1]	[2]	[3]	[4]	[5]
(1)	Year and Stock Level	0.845	[redacted]		
(2)	Year, Stock Level and Performance	0.994	[redacted]		
(3)	Year, Stock Level, Performance and Female	0.994	[redacted]	-$22.84	-1.29

Note: Models estimated on 2013-2016; year is controlled for in each model. Limited to employees who participate in the annual review process that concludes in September each year.

56. The same findings result when examining the determinants of reward bonuses. Reward bonuses are paid as a percent of eligible salary. The regression models again show that these awards are based on Stock Level and performance rating: 98% of the variation is explained by the model including performance rating, versus 44% of the variation when performance rating is excluded. As was true for stock awards, gender is a not a significant predictor of the bonus percent awarded.

Annual Review Cycle Bonus Awards (Awarded as a Percent of Bonus Eligible Salary) Rely on Performance Ratings

- 2013-2016 -

Model	**Controls**	**Adjusted R^2**	**Employee Years**	**Female Coefficient**	**T-Stat**
	[1]	[2]	[3]	[4]	[5]
(1)	Year, Stock Level	0.441	[redacted]		
(2)	Year, Stock Level and Performance	0.980	[redacted]		
(3)	Year, Stock Level, Performance and Female	0.980	[redacted]	-0.00008	-1.11

Note: Models estimated on 2013-2016; year is controlled for in each model. Limited to employees who participate in the annual review process that concludes in September each year.

57. Finally, 91.1% of the variation in merit awards is explained when performance is included in the model and only 15.8% of the variation is explained when performance is excluded. In this case, gender is a statistically significant predictor of merit awards, in that women receive higher awards all else constant, but the effect is small. There is no statistical support for Plaintiffs' revised argument that ratings and pay are somehow separate processes at Microsoft and that ratings are for some unspecified reason not biased by gender but that pay is.

Annual Review Cycle Merit Percent Raises (Awarded as a Percent of Eligible Salary) Rely on Performance Ratings

- 2013-2016 -

Model	Controls	Adjusted R^2	Employee Years	Female Coefficient	T-Stat
	[1]	[2]	[3]	[4]	[5]
(1)	Stock Level, Profession, Pay Scale Type, Tritile	0.158	[redacted]		
(2)	Stock Level, Profession, Pay Scale Type, Tritile, and Performance	0.911			
(3)	Stock Level, Profession, Pay Scale Type, Tritile, Performance and Female	0.912		0.00048	13.11

Note: Models estimated on 2013-2016; year is controlled for in each model. Limited to employees who participate in the annual review process that concludes in September each year.

PERFORMANCE: ANALYSIS OF MICROSOFT'S REVIEW CYCLE DATA

58. Plaintiffs allege that "as a result of Microsoft's forced ranking process, [the named] Plaintiff received lower performance ratings than her male peers, despite having better performance during the same performance period."[36] However, it is not empirically true that

[36] Second Amended Complaint, page 13, ¶ 62. Note that the fact pattern represented by claiming Plaintiff Moussouris had a lower rating than male peers, but had actual higher performance would be untestable with any data. If this were Plaintiffs' theory generally, there would be no data I am aware of that could possibly test the claim. This is for a simple reason: it is one thing to measure and quantify differences in performance rating, taking into account various job-related characteristics that can be measured, and identifying differences in those ratings. However, the statement in the SAC claims that her actual performance was both *higher* than her peers, and simultaneously rated *lower* than her peers. The SAC does not state she performed equal to her peers, but was rated lower. There is no way based on the data to study this – it is an untestable hypothesis. One would have to identify all of the specific work performed by the Plaintiff, and each of the peers, and then somehow determine which quantum of work was "better." This would be so individualized as to make completely intractable any kind of statistical analysis. Thus any analysis of performance ratings can only be based on identifying job-related empirical measures present in data.

women were initially ranked higher than men but that the "forced ranking" process pushed their ratings lower. Dr. Farber does not address this claim but my analysis, described below, demonstrates this. I test the Plaintiffs' assertion that Microsoft systematically downgraded female performance ratings vis-à-vis male ratings as a result of the calibration process prior to 2014. Specifically, I analyze the Performance@Microsoft ratings system data for the FY2013 ratings period.

59. I also reviewed the performance ratings for the ratings periods FY2014, FY2015, and FY2016, for any evidence of systematic downgrading of female employees' "reward outcomes", as they were called during these time periods, compared to male reward outcomes. Although Microsoft no longer uses calibrated employee ratings I extend my analysis because the complaint alleges that "Microsoft has continued to use an unreliable discriminatory performance evaluation procedure that systematically undervalues female technical employees relative to their male peers."[37] Though I understand the process is now called "People Discussions,"[38] I will continue to call it calibration for simplicity's sake.

<u>The steps and timing of the review process</u>

60. The descriptive discussion that follows is based on the cited sources, and constitutes my understanding of these elements of the ratings process. The annual performance review cycle at Microsoft typically runs from May to September of each year. The resultant rewards determined by the final ratings become effective on September 1st. Several steps in this process are recorded in a transactional database called Performance@Microsoft.[39]

[37] Second Amended Complaint, page 8, paragraph 38
[38] Ritchie deposition, Exhibit 8, MSFT_MOUSSOURIS_00004125.
[39] Deposition of John Adrian Ritchie Volume I on June 29, 2016, page 15

61. According to Microsoft documentation, during the review cycle a reviewer, depending on his or her specific role, will have differing levels of permissions in the system, which affects what can be viewed in the system, or added into the system. The primary manager roles are Direct Manager, Calibration Manager, Calibration Owner, and Human Resources. Early in the review period, employees evaluate themselves, request feedback from others, seek feedback from their Direct Managers and also provide feedback to others if requested. The employee also provides his or her Direct Manager with a list of individuals from whom feedback is requested. The Direct Manager can modify this list and after reviewing all the feedback for the employee, the Direct Manager makes an initial recommendation for the performance outcome.[40]

62. According to Microsoft documentation, performance ratings were based on three factors: (1) the employee's results and their impact on the business, (2) the context for achieving those results (i.e., how the employee compares to peers in terms of how important their results were to the business and how they worked with others), and (3) the ability of the employee to take on more challenges while maintaining results.[41]

63. It is my understanding that following the feedback period and the determination of initial recommendations, successive calibration meetings were held to make performance ratings consistent within employee peer groups. The outcome of the process also targeted a predetermined distribution of ratings. It is also my understanding that the idea behind forced, or "stacked ranking" systems is that employees must fall into a pre-determined distribution (for example, 20% top ranked, 70% in the middle, 10% at the bottom). Even if some employees are ranked "top" by their direct manager, they might end up in the middle 70% as the ranking process begins to incorporate comparisons across greater numbers of employees (i.e., what is

[40] Deposition of John Adrian Ritchie Volume I on June 29, 2016, pages 153:233
[41] Deposition of John Adrian Ritchie Volume I on June 29, 2016, pages 113:119

referred to at Microsoft as "calibration"). Prior to 2014, Microsoft's performance review system included a calibration process by which the direct manager's initial recommended ratings were reviewed by higher level managers who could raise or lower or accept the employee performance ranking to conform with their overall business directives. Their calibration would largely affect those employees who were on the "cusp" between ratings. Some employees' ratings would have moved up or down to approximate a predetermined distribution of final ratings.[42]

64. Direct Managers apparently do not participate in the calibration meetings, but rather, they provide the information and recommendation to a Calibration Manager who represents multiple Direct Managers in the calibration meeting.[43] Successive calibration meetings, which serve to roll up or combine calibrations or to discuss high level peer groups, can occur multiple times within an organization.[44] Thus, someone who is a Calibration Owner leading one calibration meeting may be one of several Calibration Managers participating in a subsequent meeting.

65. It is my understanding that the Calibration Owner and HR had discretion in choosing the method by which Employees were ranked or rated in the calibration meetings. The stack ranking approach described in the complaint was one methodology, while the ratings approach was an alternative method. Under the stack ranking approach, employees were ranked in order from low to high. Alternatively under the ratings approach, the initial recommendations were considered, and ratings were adjusted up or down for employees who were on the "cusp" between ratings in order to achieve a pre-determined ratings distribution. Employees' ratings were adjusted until the recommended distribution characteristics were met.[45]

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[42] Deposition of John Adrian Ritchie Volume I on June 29, 2016, page 159
[43] Ritchie Exhibit 3 (MSFT_MOUSSOURIS_00002273)
[44] Deposition of John Adrian Ritchie Volume I on June 29, 2016, page 207
[45] Deposition of John Adrian Ritchie Volume I on June 29, 2016, page 159

66. Following the finalization of the employee's performance outcomes, the Performance@Microsoft system was closed to further input and rewards were determined. The feedback was communicated from Calibration Managers back to Direct Managers, who would have an end of the year performance assessment with their employees to discuss their performance outcome as well as the associated rewards.[46]

Overview of the Performance@Microsoft database

67. The Performance@Microsoft system database contains transactional data entries that occur throughout the review cycle. A data record includes the reviewee's personnel number, the time and date of the entry, the type of action being taken, a performance rating, an alias for the person updating the record, an alias for the current approver, and other information.[47]

68. These data give an overview of the underlying performance process showing changes in performance rating over time associated with different "current approvers." Those current approvers may make, or oversee, several consecutive changes in the performance ratings before the active current approver changes. The records may show several changes in current approver until there is a final approval transaction.

69. For each employee, the first entry with a performance rating usually occurred in early July, and was generally initiated by the "rewards manager" or a member of HR with the "rewards manager" listed as the "current approver".[48] The complaint makes a specific claim within the class period that "in May 2013, Plaintiff's manager … told her she deserved a 1 [but]

[46] Deposition of John Adrian Ritchie Volume I on June 29, 2016, pages 240-243.
[47] The database field is called "commitment rating" but the values correspond to the "performance rating" field as recorded in the job history files.
[48] There are some cases where the rewards manager changes. This happens for about 11% of employees in FY2013. My main analyses ignore these changes but the results are robust to replacing the first rewards manager ratings with several other proxies.

Plaintiff received a 2."[49] The database corresponds to the Plaintiff's assertion, showing that she was listed as a 1 beginning on July 1, 2013 but was changed to a 2 on July 18, 2013. The current approver for that change was not her rewards manager but one level higher in the process. The analysis reported on here will show that this anecdote was an exception to the rule with respect to gender.

70. The data does not contain any information about conversations managers had with their employees before the calibration process began. I use the performance rating that was in effect at the time when the "current approver" first changed from the reward manager as the initial rating.[50,51] I then analyze the difference between the initial performance rating and the final performance rating, as recorded in the September Job History file.[52]

71. For my analyses, I restrict the profession to be either Engineering or IT Operations and Stock Level to be in the range of 59 to 67, following Dr. Farber's analysis. Similarly, following Dr. Farber, I exclude records where Career Stage is equal to ATR-C, ATR-D, ATR-E, IC-0 or MA. In fiscal year 2013, employees received a performance rating which ranged from 1 to 5 (with 1 being the highest result). In contrast, the reward outcome measure used in fiscal years 2014 to 2016 [redacted]

[49] Second Amended Complaint, page 13, paragraph 64

[50] This is the first time this occurs because there are times when the records are passed back to the rewards manager and changes are made to the performance rating. There is also a sparsely populated field called "recommended commitment rating" that matches this initial rating in most cases. When the recommended commitment rating is not missing (for 1,121 employees in 2013), it matches the rating left by the first current approver 91% of the time.

[51] The findings presented below are robust to the inclusion of other definitions of the direct manager's initial ratings. Specifically, I replaced the value left by the first manager with the following: the first, average, minimum, maximum, and mode of all recorded scores, and then the first, average, minimum, maximum, and mode of the first manager's recorded scores. The sensitivity analyses reveal no evidence of systematic adverse differences for women during the calibration process or the reward determination cycle.

[52] I used the final performance rating as obtained from the September 1st entries in the Job History File. The analyses exclude 497 review cycle employees who were not present on September 1st, 8 employees with a September 1st record but no review cycle record, and 9 employees in the review cycle data not found in the job history files.

[redacted] Therefore, to make the presentation of the results consistent over the two periods, [redacted] in the Performance@Microsoft data in my analyses.

Overview of the "Performance and Development" program

72. Microsoft redesigned its performance management system for review cycles and implemented the "Performance and Development" system in fiscal year 2014.[53] This was a different way of providing feedback to employees and allocating rewards. Along with the new approach, a new process management system called the Managed Rewards Tool (MRT) was developed for the rewards allocation process.[54]

73. The new system represented a change in Microsoft's approach to performance management. Instead of an annual review cycle, where employees were rated through a calibration process, the new approach involves feedback discussions throughout the year that contribute to the annual rewards allocation process. Unlike the previous system, where performance ratings were communicated to the employees along with their rewards, only the rewards are now communicated.[55]

74. In the MRT system, managers make reward recommendations by moving an impact slider that translates into specific reward outcomes. The direct manager makes the initial recommendation and discusses the recommendation with higher level managers. These more senior managers may participate in "People Discussions" where initial impact recommendations across the organization are reviewed and discussed. Following these discussions, the senior managers may make adjustments to the impact slider positions. The impact recommendations

[53] Deposition of John Adrian Ritchie, Exhibit 11.
[54] Declaration of Larrissa Johnson.
[55] Deposition of John Adrian Ritchie, Volume I, pages 240-243.

from the senior managers are then "rolled up" to the organization leader who has the ability to adjust the impact sliders with respect to allocating the budget.[56]

The "Performance and Development" database

75. The MRT database identifies changes in the impact slider position and the corresponding reward outcome level.[57] Similar to the Performance@Microsoft, a data record includes the reviewee's personnel number, the time and date of the entry, the type of action being taken, reward outcome, the person updating the record, the "manager in control", and other information.[58]

76. The reward outcome variable takes [redacted], which when finalized factors into reward amounts for [redacted] depending on various eligibility criteria and job characteristics. [redacted].[59]

77. I study whether there was any systematic downgrading of reward outcomes for women relative to men since FY 2014.[60] Similar to the analysis for the fiscal year 2013 Performance@Microsoft review period, for the starting value I chose the reward outcome that was in effect at the time when the field "manager in control" first had a change in the user ID.

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[56] Deposition of John Adrian Ritchie Volume I on June 29, 2016, pages 234-235.
[57] The range of possible values for the impact slider is 0.0 to 100.0.
[58] I ignore system update entries identified by updated_by=SYSTEM and action=Extract, when there is no change in reward outcome. There are a large number of those records that do not represent any actual review activities. The inclusion of those records would affect the calculation of averages, medians and modes of the outcome measures.
[59] Letter from Orrick, Herrington & Sutcliffe LLP to Plaintiffs' counsel regarding "*Moussouris v. Microsoft Corporation*, W.D. Wash. Case No. 2:15-cv-01483 (JLR)" dated December 6, 2016, page 2.
[60] Deposition of John Adrian Ritchie Volume I on June 29, 2016, pages 240-243.

78. For my analyses, I again restrict the profession to be either Engineering, or IT Operations and Stock Level to be in the range of 59 to 67. In addition, like Dr. Farber, I exclude records where Career Stage is equal to ATR-C, ATR-D, ATR-E, IC-0 or MA. Finally, I restrict the analyses to those who are flagged as rewards eligible.[61]

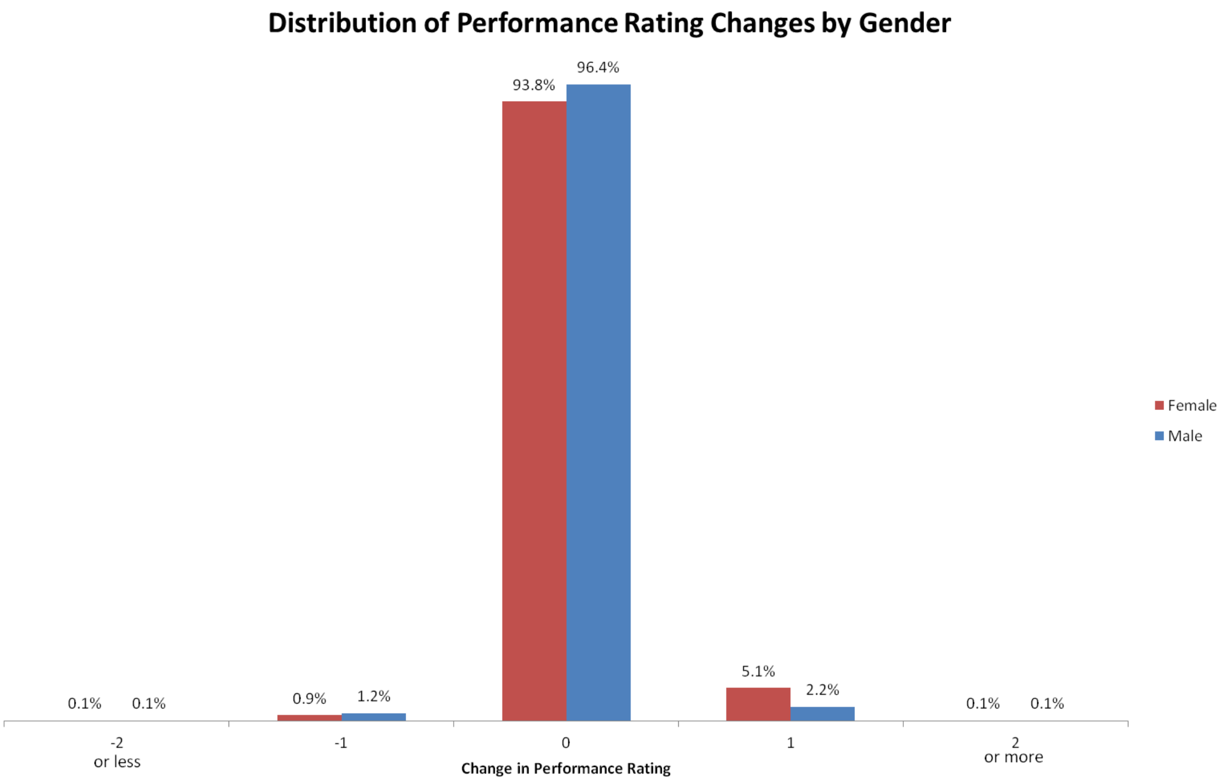
79. Similar to the previous section, I obtained the ultimately assigned reward outcome from the September 1st entries in the Employee Job History file.[62]

<u>The analysis of performance rating changes shows that women were not more likely than men to be downgraded during the calibration process</u>

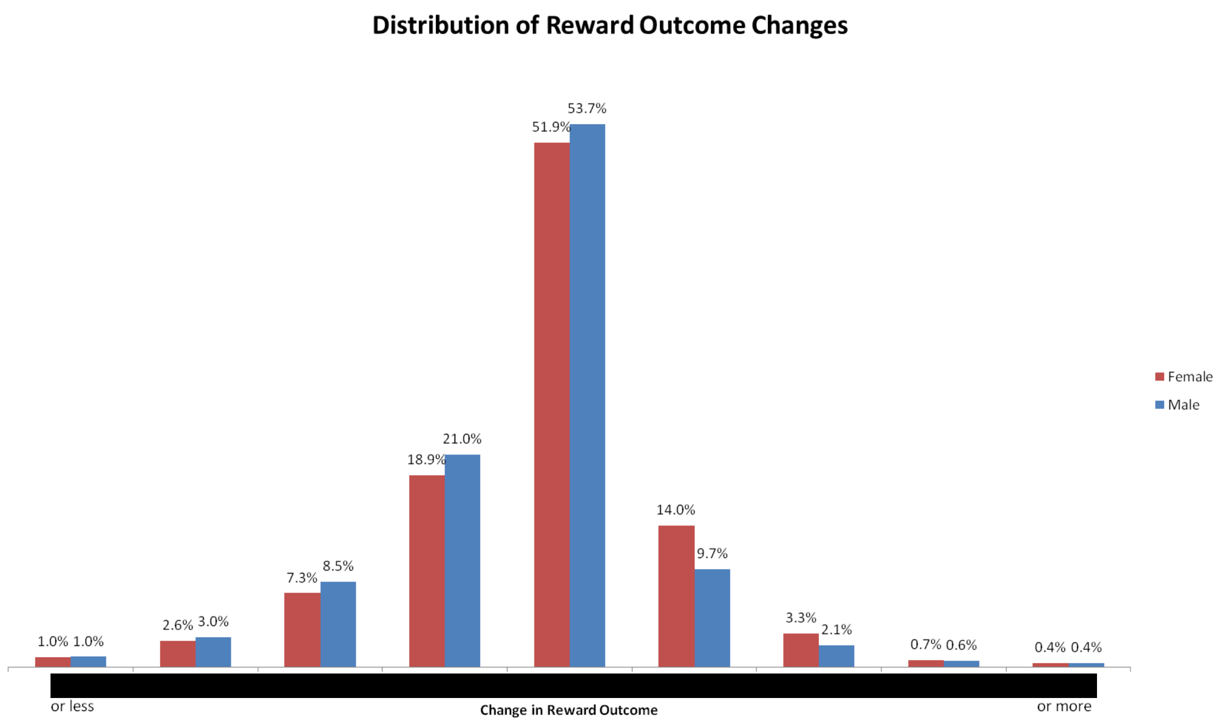
80. During the fiscal year 2013 Performance@Microsoft period, only 4% of employees' recorded performance ratings changed over the course of the calibration process. Most of those changes represented an improvement in ratings of one point. A one point movement up or down is consistent with the practice that only employees on the cusp between ratings were the focus of the calibration process. Figure 1 demonstrates that women were more likely than men to receive an upgrade in their rated performance during the calibration process (5.2% compared to 2.3%) and were slightly less likely to receive a downgrade (1.0% compared to 1.3%).

[61] See MSFT_MOUSSOURIS_00308268.

[62] I exclude from analyses only 11 employees not matched to a September 1st record for FY2014, 5 for FY2015, but none for FY2016. Furthermore, I remove any records where the September 1st reward outcome is missing or equal to zero ("0") leading to 352, 58, and 58 additional records excluded for FY2014, FY2015 and FY2016, respectively.



81. Under MRT, the review ratings [redacted]. The result was that since FY2014, 47 percent of employees had reward outcome changes over the course of the reward determination cycle. Figure 2 shows the distribution of these changes between men and women. Women were more likely than men to have received an increase in their reward outcome factor; specifically, about 18 percent of women saw an increase in the reward outcome while only 13 percent of men saw an increase. Moreover, women were also less likely than men to have received a decrease in reward outcome; specifically, 30 percent of women and 33 percent of men received downgrades.



82. More formal statistical tests confirm what these figures show, that in contrast to Plaintiffs' hypothesis, women are not more likely to be downgraded than men. The evidence also does not show that women are rated higher initially and then systematically downgraded during calibration. The first row of the table below compares the average calibrated Performance@Microsoft rating changes in fiscal year 2013 across gender utilizing t-tests of statistical significance.[63] On average, both men and women received better scores than initially recommended by their rewards managers as shown by the positive changes in the average ratings. However, women received slightly bigger increases than men on average. These findings do not support the claim that women were downgraded more relative to men during the performance calibration process in fiscal year 2013.

[63] A t-test of the difference in the averages from two samples of data identifies the number of standard deviations of difference between the averages. Statistical significance is associated with differences greater than 1.96 in the absolute value of the t-statistic.

Comparison of Average Changes in Review Cycle Outcomes for Female Employees Compared to Male Employees

Fiscal Year	Review Cycle Measure	Female Employees		Male Employees		Difference in Average Value Change (Female - Male)	T Stat
		N	Avg Change	N	Avg Change		
[1]	[2]	[3]	[5]	[6]	[7]	[8]	[9]
2013	Perf. Rating	[redacted]	0.041	[redacted]	0.007	0.033	8.0
2014	Reward Outcome	[redacted]	-0.483	[redacted]	-0.591	0.108	6.1
2015	Reward Outcome	[redacted]	-0.144	[redacted]	-0.257	0.113	6.6
2016	Reward Outcome	[redacted]	0.004	[redacted]	-0.154	0.157	10.2

Notes: For each regime, the change in value is measured as the difference between the value left by the first manger in control and the final value recorded in the Job History file

83. The next three rows of the table compare the average change in the reward outcome measure across gender during the MRT period. During fiscal years 2014 and 2015, men and women on average received decreases in reward outcome during the reward determination cycle but the reduction was less so for women than men. In fiscal year 2016, women experienced a slight increase in reward outcome of 0.004 points on average while men received a 0.154 point average decrease in reward outcome. All of the results are statistically significant in favor of women for all years, though the differences in practical terms are quite small.[64]

84. I conducted similar mean comparisons of the review outcome measure for both the Performance@Microsoft and MRT regimes by profession and Career Stage. All but one of 44 results are either neutral or favorable to women.

85. The analysis presented in the table above simply compares the mean changes in performance ratings or reward outcomes between men and women. To more directly test the

[64] In this case, the numbers of observations in the analyses are large, and the distribution of values quite confined, both of which contribute to a conclusion of statistical significance in even small differences between the figures involved.

Plaintiffs' assertion that women were more likely to be downgraded in the calibration process, I run the Chi-square test of independence and compare the relative odds of a downgrade given gender.[65] The downgrade variable is equal to one if there was a decrease in performance rating or reward outcome during the cycle, and is equal to zero if there was an increase or no change. The table below reports these Chi-square results and associated odds ratios. The Chi-square tests shows that there is a statistically significant gender difference in the probability of a downgrade in all years in the class period. I calculate the odds ratios to measure the magnitude and direction of this relationship. In fiscal year 2013, the odds of a man being downgraded were 1.40 times the odds of a woman being downgraded during the calibration process. Similarly, during the MRT period, the odds of a man being downgraded were between 1.13 and 1.32 times the odds of a woman being downgraded during the rewards determination cycle.

Test of Independence Between Review Cycle Downgrades and Gender

Fiscal Year	**Review Cycle Measure**	**Odds ratio (Male:Female)**	**Chi-square Test Statistic**	**P Value**
[1]	[2]	[3]	[4]	[5]
2013	Performance Rating	1.40	5.928	0.015
2014	Reward Outcome	1.17	27.001	0.000
2015	Reward Outcome	1.13	11.601	0.001
2016	Reward Outcome	1.32	57.577	0.000

Note: A downgrade is coded 1 if the performance rating falls during the review cycle; equals 0 if not.

86. I further tested the probability of a decrease in the rating or outcome measure by gender using a probit regression analysis, in which the outcome measure is a downgrade as defined in

[65] A Chi-square test compares the distribution of a given population along two dimensions, in this case, rating change, and gender. The question is whether or not changes in ratings are associated with, or are independent of gender. The result of the test is a p-value. If the p-value is less than 0.05, we say that there is a statistically significant relationship between gender and ratings adjustment, such that we reject the hypothesis that gender and ratings adjustment are independent.

the previous paragraph. I estimated three general models, first controlling only for gender and then adding profession and Career Stage. The models controlling for only gender are statistically significant and in favor of women for the four years in the class period. Women were about 13 percent less likely than men to receive a downgrade in performance rating and 7% to 16% less likely to receive a decrease in reward outcome when only gender is used as a control. The models with additional controls also yield negative coefficients for women, meaning women have a lower probability of a downgrade. However, the results are not significant during fiscal year 2013. In the MRT period, every model yielded statistically significant results that were favorable to women. Those models suggest that women experienced between a 7% to 17% lower probability of receiving a downgrade than men.

87. In conclusion, there is no empirical evidence that the performance review process is biased against women. Final ratings are not different between men and women, and the slight changes that occurred to both men and women during the calibration cycles over the years were neutral or slightly favored women. Thus Plaintiffs' claim that the common causal connection between gender differences in pay and promotions is the performance evaluation process is not supported by the data.

88. I turn next to the analysis of promotions.

PROMOTIONS

89. There are a number of flaws with Dr. Farber's analysis of promotions. Once these flaws are corrected to the extent permitted by the available data, the shortfall in female promotions is very small, and the selection rate of women is 98% that of men. As noted above, as a threshold matter Dr. Farber did not restrict his analysis of promotions to the class period. His computed

shortfall of 518 female promotions falls to 337, with no other changes to his statistical model, simply by restricting to the class period.

90. Beyond the timing issue, there are a number of substantive flaws with Dr. Farber's promotion analysis. First, Dr. Farber inappropriately combines the IT Operations and Engineering professions in his analyses. Compensation at Microsoft is arranged within professions, and different professions map to Stock Levels differently. A level 61 employee in Engineering, for example, tends to be younger than a level 61 in IT Operations, presumably because the market competition for junior engineers is higher. As a consequence, the Engineering profession is mapped to higher Stock Levels than the IT Operations profession.[66] This is a concern in promotion analyses, because the movement from level 61 to 62, for example, is a more senior career move in IT Operations than in Engineering. My analyses are thus estimated separately by profession.

91. Another flaw in Dr. Farber's analysis is that it does not control for the correct tenure measure. What matters for promotions from one level to the next is tenure in current level, not just age and *overall* tenure at Microsoft. The reason labor economists focus on time in level is that additional time in level is associated with increases in human capital as employees gain increased skill and facility with their work over time at that level. Thus it is expected that higher tenure in job is associated with an increased probability of promotion to a higher job. Indeed, the MS People data tracks the number of months since an employee's last promotion and the number of months an employee has been at his/her Stock Level.[67] My analyses take into account time in stock level when analyzing movements from stock level to stock level.

[66] MSFT_MOUSSOURIS_0004282.

[67] The MS People contains variables indicating the number of months since an employee's last promotion ("Months_Since_Last_Promo") and the number of months an employee has been at his/her Stock Level ("Stock_Level_Month_Qty").

92. In addition, Dr. Farber does not model the actual promotion process but instead relies on aggregated year-to-year changes as a kind of "bottom line." [redacted][68] Here I find that there is no gender difference in promotions for employees in the IT Operations profession. I find a small promotions shortfall among employees in the Engineering profession. The same decision makers are likely to be involved in promotions, regardless of the time of the year, and these decision makers rate women equally to men and promote women equally to men for the almost [redacted] of promotions that take place during the annual review period. Based on my review of the promotion justifications, those completed at times other than the annual review appear to be equally thorough to those completed during the annual review.[69] However, as I will show below, there are a number of idiosyncratic factors present in connection with non-annual review promotions for which there is no systematic data. The inference is that the nature of the missing information relative to mid-year/other situations likely correlates to gender, such that if we had that information it might serve to explain whatever measured gender differences are observed for those periods of time. The next sections explain in detail each of the flaws in Dr. Farber's approach to promotions, and their impact on his conclusions.

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[68] "Promotions usually occur mid-year or at the end of the fiscal year. At any time of the year, employees are eligible for promotion." Statement to the OFCCP by John Ritchie, December 16, 2014. MSFT_MOUSSOURIS_00308280. Many managers avail themselves of non-annual opportunities to promote employees. According to the data, [redacted] of supervisors have promoted one or more employees at some time other than the annual review cycle process.

[69] In fact, a simple comparison of average word count showed that the justifications entered during the annual review process have statistically significantly fewer words than those entered at other times of the year.

Tenure is incompletely defined in Dr. Farber's promotion model specification, and he includes data from outside the class period in his analyses

93. In Table 6 of his report, Dr. Farber presents the results of his analysis of Stock Level advancement utilizing a multivariate probit approach. Dr. Farber uses these results to calculate the probability of Career Stage or Stock Level advancement for women, and thereby estimates female promotion shortfalls. The variables Dr. Farber uses in his model are "experience at Microsoft, experience at Microsoft squared, age and age squared, Discipline, city and state of work, previous stock level, and performance metrics."[70] However, time in current position is not included, and this is probably the most the relevant tenure measure.

94. While Dr. Farber does not control for time in Stock Level or time in Standard Title in his analyses in this case, this is in contrast to the promotion models he estimated in his report in *Chen-Oster, et al., v Goldman Sachs*, where he did control for time in current position at Goldman.[71] These more "job specific" measures of tenure are highly relevant to a promotion analysis. In my experience as a labor economist analyzing internal movements within companies, this is generally true in any company, whether they use seniority or merit promotion practices. By not using time in level, Dr. Farber's analysis treats an individual who was just promoted into a particular level and another who has been in that level for several years as similarly situated with regard to promotion probability. This is not likely to be the case.[72] In

[70] Report of Dr. Henry Farber, p. 33, ¶72.

[71] In his analysis of promotions to Managing Director, Dr. Farber included time as a VP and time as a VP squared in addition to their overall time at Goldman. "I estimate the probit model of the likelihood of promotions as a function of year, the same **number of years as Vice President**, division, office, education, AA job group, experience at Goldman, experience at Goldman squared (both from the most recent hire date), relevant experience prior to most recent date at Goldman (including experience in prior periods of employment at Goldman), relevant experience squared, and whether a direct hire into the VP position." Expert report of Henry S. Farber in connection with *Chen-Oster v. Goldman Sachs*, February 17, 2014, page 32 and Table 20. Emphasis added.

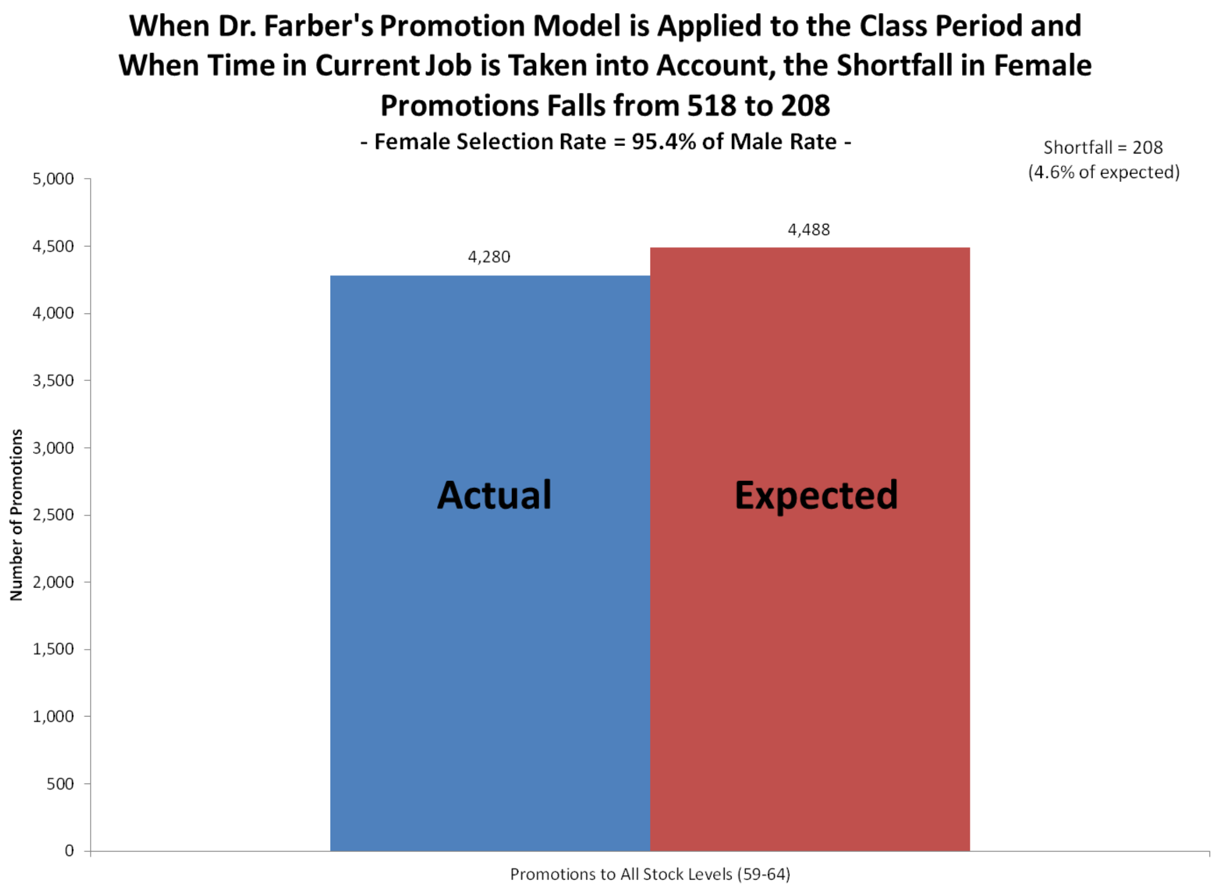
[72] Consider as well that the "time at Microsoft" measure he utilizes includes time in different employment

addition, two persons with widely differing total time at Microsoft or very different ages but each having the same time in current job would be treated incorrectly in a model like Dr. Farber's which only controls for overall Microsoft tenure. Constructing time in level and title measures is straightforward based on the information in the MS People job history.

95. In order to perform a proper comparison, I ran Dr. Farber's model including only the time period covered by the Class definition, i.e. advancements in salary years 2013 through 2015 and added variables that measure time in Stock Level and time in Standard Title.[73] The marginal effect of being female drops from -0.021 estimated in Farber's original model to just -0.015. The estimated shortfall in female Stock Level advancements falls from 518 to 208 simply by restricting the analysis to the class period and using the appropriate tenure variables. A shortfall of 4.6% is relatively small compared to total female expected advancements of 4,488. The chart below depicts the actual and expected number of promotions, correcting Dr. Farber's model only for the use of current level and title tenure measures and restricting to the class period.

spells. For example, if someone worked at Microsoft for 5 years, left for 10 years, and returned, their "time at Microsoft" upon return would be 5 years. That time is less directly relevant to the likelihood of promotion in any given year of the return period of work.

[73] Squared tenure terms are also included. Note that the class period begins in September 2012, and thus the end of the first fiscal year within which promotions can be identified is September 2013. Also, the data provided during discovery cuts off before September 1, 2016, which means the last completed year for analysis is fiscal 2015.



<u>Dr. Farber inappropriately aggregates across professions which have their own career paths</u>

96. A profession is defined at Microsoft as, "A collection of multiple related disciplines with common success differentiators (competencies) and management requirements, often associated with formal education, such as Engineering, Sales, or Marketing. A profession provides a basis for a career path."[74] In general, there is little crossover between the two professions, which is consistent with having distinct career paths. In 2016, Microsoft reorganized by reducing the number of employees in IT Operations and moving some into Engineering. Even including that reorganization, just 4.3% of employees from 2013-2016 changed between IT Operations and Engineering; excluding that last year, just 1.6% did so. Professions are also mapped to levels

[74] Declaration of Martin Loughlin, p. 17.

differently, meaning that a promotion from Stock Level 63 to Stock Level 64, for example, can be a more "senior" promotion for one profession than it is for another. On the whole, IT Operations is mapped to lower Stock Levels than Engineering. Despite this, Dr. Farber combines employees in the Engineering profession with those in IT Operations in his analyses.

There is no gender difference in promotions in the IT Operations profession

97. The table below shows the results of studying promotions separately by profession, but still utilizing Dr. Farber's probit methodology. The first row combines the two professions, adds the current job tenure variable and uses the correct class period definition, and shows a marginal effect of being female of -0.015 in column 6. The second row shows the results for IT Operations: there is no difference by gender. In fact, there are a few more promotions of women than the model predicts. This is in contrast to Dr. Farber's assertion or implication that the average effect he finds is a common one – clearly it does not apply even in the aggregate to female employees in IT Operations. The third row shows the results just in Engineering: a marginal effect of -0.017, which though small is statistically significant.

Running Dr. Farber's Promotion Analysis by Profession Shows NO Gender Difference in IT Operations - 2013-2015 -

Population Analyzed	Employee Years	Number of Female Employee Years	Number of Promotions	Number of Female Promotions	Difference (Marginal Effect)	Z-statistic
[1]	[2]	[3]	[4]	[5]	[6]	[7]
Both Professions	[redacted]	[redacted]	25,054	4,280	-0.015	-4.364
IT Operations Only	[redacted]	[redacted]	1,570	323	0.004	0.427
Engineering Only	[redacted]	[redacted]	23,484	3,957	-0.017	-4.811

Note: The probit model is estimated only over the class period, 2013-2016. It controls for tenure in Stock Level, tenure squared, age, age squared, year, performance, location, discipline, and prior Stock Level. Promotions are identified when Stock Level of current year is lower than Stock Level of following year, following Dr. Farber's approach.

98. From a statistical perspective, based on Dr. Farber's approach women in the IT Operations profession do not share a common experience with those in Engineering. Below, I examine promotions in Engineering in more detail. Before I do so, however, I make an additional correction to Dr. Farber's approach to handling the data in order to include all promotions in the analysis and not just year-to-year changes.

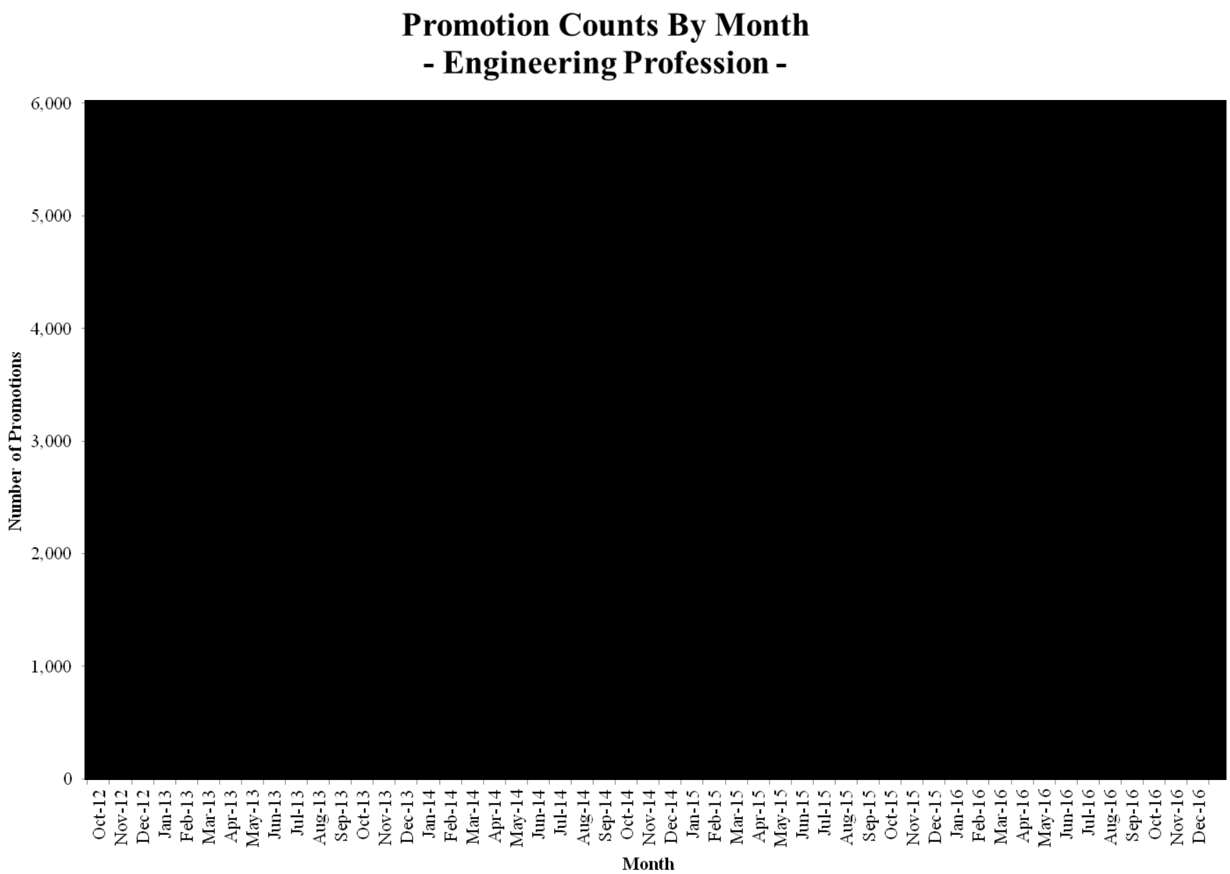
Dr. Farber does not use the promotion indicator contained in the data

99. Dr. Farber defines promotions by comparing employee stock levels at adjacent year ends. He does not use the promotion indicator that is contained in the Microsoft data. Thus, he cannot analyze promotions occurring at different points in time during the year.[75]

100. Using the effective date for promotion means the time pattern of promotions can be examined. As noted above, there are two general categories of promotions: those referred to as "annual," which occur in connection with the annual performance review cycle, and which all are effective on or very close to September 1, and those referred to as "mid-year/other," which can occur at other times of the year.[76] I limit the promotions in the chart below to Engineering profession employees, but a similar pattern is evident for those in IT Operations. I will focus my attention in the following discussion on the Engineering profession, given that there is no gender difference in promotions in the IT Operations profession.

[75] Using adjacent year ends also can result in missing promotions for those employees not present at adjacent year ends.

[76] Dr. Farber defines an "advancement" as either an increase in stock level or an increase in career stage from one year to the next (Report of Dr. Farber, paragraph 21). In fact, Microsoft uses a specific indicator to show when a move is classified as a promotion, that I can then use to examine promotions at various times of the year. In the MS People job history data, promotions are coded as "Promotion Change Indicator = Y". The Microsoft promotion indicator identifies a larger number of promotions than Dr. Farber's approach of comparing adjacent year ends from September 2010 through June 2015 (46,038 vs. 40,812). However, the proportion of promotions that go to women is virtually identical under the two definitions: 17.27% vs. 17.25%. Every "P" change is accompanied by a stock level change. This suggests that the analytical findings of using the "P" indicator as opposed to year end snapshot comparisons is unlikely to impact the nature of the findings, and is more complete and appropriate to capture all promotions.



101. The annual versus mid-year/other distinction turns out to have major consequences for identifying the relationship between gender and promotion practices in Engineering. I analyze the data using the same probit models as above with one additional correction, which relates to how Dr. Farber utilized performance ratings. This is because a promotion in March (for example) is not dependent on a performance rating that is issued the following September. Instead, for mid-year/other promotions, I assign the performance rating in place the *previous* September.

<u>Dr. Farber does not assign the correct performance rating in his analyses because he ignores promotion timing</u>

102. In order to control for performance, Dr. Farber matches the performance rating from the current fiscal year's review cycle to the promotion decision in that same year. However, since he does not separate the annual process from the mid-year/other process, there is a mismatch between performance ratings and promotion decisions for the mid-year/other promotions. At the time mid-year promotions decision are made (mid-fiscal year), the end-of-fiscal-year performance review cycle has not yet been completed. Therefore, the only official information that would be available to decision-makers regarding performance ratings would be from the *prior* year. Dr. Farber's combining annual and mid-year/other promotion decisions causes his model to mis-apply mid-year/other decisions to a performance score which has not yet been assigned, for performance which has in fact not yet happened.

103. Additionally, it is not proper to group these two promotions in the same fiscal year because they fall under different promotion budgets. It is my understanding that an annual promotion budget is set and approximately [redacted] of that budget is allocated for annual review related promotions. The remaining [redacted] plus any surplus or shortfall left over *after* the annual cycle promotions is then allocated for promotions taking place at other times of the year.[77] A March 2015 promotion, for example, would fall under the FY2014-2015 budget, and the September 1, 2015 promotions would be part of FY2015–2016.

[77] Declaration of Larissa Johnson on May 2, 2016 p. 5. See also MSFT_MOUSSOURIS_00004285.

There is no gender difference in promotions in the Engineering profession during the annual review process

104. The table below provides the overall results for Engineering and then breaks these results out separately by the annual and mid-year/other periods.[78]

Running Dr. Farber's Promotion Analysis by Time Period During the Year Shows NO Gender Disparity for the Annual Review Process, Which Covers Almost [redacted] of All Promotions

- Engineering, 2013-2015 -

Population Analyzed	Employee Years	Number of Female Employee Years	Number of Promotions	Number of Female Promotions	Difference (Marginal Effect)	Z-statistic
[1]	[2]	[3]	[4]	[5]	[6]	[7]
Overall	[redacted]	[redacted]	[redacted]	[redacted]	-0.017	-4.811
Annual Review Cycle					0.003	0.793
Mid-year/ Other					-0.018	-6.173

Note: The probit model is estimated only over the class period, 2013-2015. It controls for time in stock level (and squared), time in standard title (and squared), year, performance, location, discipline, and prior stock level. Promotions are identified when stock level of current year is lower than stock level of following year, following Dr. Farber's approach.

105. As can be seen from looking at the tables, only the Engineering profession mid-year/other cycle shows a statistically significant shortfall of promotions for women. The annual review promotions show no gender difference in promotions.[79]

[78] Using the "P"-code found in the MS People job history data.
[79] The same analysis for IT Operations shows no gender difference overall, nor when separated into

106. It is important to note that only annual promotions are conducted in connection with the performance review process, which as seen in Dr. Farber's as well as my analysis is gender neutral. Thus, the gender neutral performance evaluation process apparently leads or could be considered causal to the outcome of a gender neutral promotion process. However, it is my understanding that mid-year/other promotions are not connected with the annual performance process, and can occur for a variety of idiosyncratic reasons that may not be present during the annual review periods, such as to retain employees who receive outside job offers, or for various business-related reasons. Consequently, the variables available in the data produced to include in a statistical model may be appropriate for aggregated analysis of the annual review promotion decisions, but they may be inadequate for the mid-year/other events, since there are factors outside of performance rating alone that also may be important, and for which Dr. Farber has presented no data or variables.

107. For example, if one reviews the promotion justification comments associated with mid-year/other promotions, they are different in character than those for annual review promotions. In particular, one sees business reasons cited more frequently in the promotion justifications. Nevertheless, as I show in further detail below, when mid-year/other promotions are studied correctly, by taking into account supervisor differences, there is virtually no shortfall in these types of promotions. I also further demonstrate that, unlike in the case of annual review promotions, the types of issues involved in fully addressing mid-year/other promotions are likely to be highly individualized.

annual versus mid-year/other promotions.

Idiosyncratic "business need" justifications in the performance evaluation materials are more likely in mid-year/other reviews

108. The description of mid-year/other promotion activity in depositions and elsewhere in the record suggest that these promotions have a more individualized quality than the promotions during the annual review. To study this, I analyzed the distribution of "promotion justification" reasons separately for annual and mid-year/other promotions. Promotion decisions at Microsoft are documented in the performance audit files. I studied the information in the audit file to determine the reason for each promotion.[80] While the justification for some promotions focuses on the individual characteristics of the promotee (e.g. personal skills and accomplishments), other promotions appear to also be initiated for business reasons (e.g. expected product growth, retention concerns). The hypothesis was that mid-year/other promotions were more likely to be related to business reasons than are promotions that occur during the annual review. This implies that the decisions are made for more individualized reasons, responding to idiosyncratic business and external factors more so than promotions awarded in connection with the annual performance review process. Considering the very small shortfall in actual female promotions relative to the number expected, the gender difference in idiosyncratic business driven promotion reasons would not have to be large to explain the small gender shortfall in promotions.

[80] Comments related to promotion justification can be found in the MRT audit files, which track the status of rewards or promotions over the course of the decision. I received one audit file for mid-year/other promotions (MSFT_MOUSSOURIS_00752990) from the MRT. I also received three separate audit files for annual promotions from the MRT—one for each year (2014 Highly Confidential AEO.txt, 2015 Highly Confidential AEO.txt, 2016 Highly Confidential AEO.txt). These files contain a field called "Promotion Justification Comments" which has the comments inputted by managers explaining why they recommend a promotion. I examine the last audit record for each employee, fiscal year, timing of promotion, where the Promotion Justification Comments field is filled in. Furthermore, I cross reference the audit file with the promotions identified from the MS People Job History data to limit the analysis to only promotions that were successful—in other words, the promotion was approved.

109. I searched the promotion justification variable for different phrases that would indicate a promotion made for business reasons, such as [redacted] Among the 22,248 successful promotions I studied, I found that 8.2% included promotion justification comments related to business reasons. However, among mid-year/other promotions, business reasons were provided 10.6% of the time, whereas just 7.2% of the annual review promotions included these types of comments. This difference is statistically significant and sizable in relative terms – mid-year/other promotions are 47% more likely to contain business reason commentary.

110. Another notable fact about promotions related to business needs is that business reasons generally become more frequent in promotions as employees move up the hierarchy. In the performance audit files, the resulting promoted-to salary grade level ranges from 60 to 65. As the salary grade level increases, the proportion of promotions related to business need also tends to increase. In each level except for level 65, though, mid-year/other promotions continue to be statistically significantly more likely than annual review promotions to be associated with business need. It is also interesting to note that as "promotion to" level increases, the incidence of business reason commentary converges across review periods. This suggests that the higher level the promotion, the more likely the employee in question bears a more significant relationship to business drivers. The results of this analysis are shown in the graph below:

111. To sum up the implications of the analysis of these various subsets of promotions, it would be a difficult and mutually inconsistent argument to suggest that Microsoft decision makers would choose to make adverse promotion decisions against female engineers during the mid-year/other period, but not during the annual reviews, and also not to make adverse decisions for females in the IT Operations profession regardless of promotion timing. As discussed above, there are a number of unknowns regarding the mid-year/other promotion process, while the annual review process is more fully documented. I turn next to an analysis of how decision makers (supervisors) factor into promotion outcomes for women, which Dr. Farber does not address in his report, and I show that once supervisor effects are factored in, the shortfall in female promotions falls to very small levels. The implication from these findings is that there is

little to no inconsistency: Microsoft rates the job performance of men and women the same, and promotes them in extremely close to the expected numbers for all practical purposes.

VARIATION IN PROMOTION PROCESS CONTROLLING FOR MANAGERIAL EFFECTS

112. The discussion above examines several scenarios where promotions are aggregated, but does not examine how women fared when you look at outcomes by decision maker. This section will demonstrate that even within the aggregated annual review results, there is wide unexplained and likely idiosyncratic variation in outcomes at the approving manager level. I will also demonstrate that once decision makers are factored into the analysis, the female shortfall identified in certain areas identified above falls to very low levels which have no practical significance.

113. As noted above, promotions occur throughout the year. Only the promotions that are completed in September are directly connected to the annual review process. However, mid-year/other promotions also move through a series of managers for approval.[81] It is my understanding that different businesses in Microsoft vary in how they process mid-year/other promotion decisions, and which manager levels are required for approval.[82] [redacted]

[81] For all promotions, managers need to consider the criteria of business need, employee performance, and budget availability (Deposition of John Adrian Ritchie Volume II on June 30, 2016 p. 495:20 – 496:7. However, there are differences in process. For example, managers may discuss a nomination with their manager before entering submitting the nomination into the tool (Ritchie Exhibit 44 MSFT_MOUSSOURIS_00004283). The requirements for promotion approval are also determined by each business. Some may require two levels of management approval. Others may require more levels of approval. This hierarchy of approval may not be the same as the hierarchy during the annual review process.

[82] Deposition of John Adrian Ritchie Volume II on June 30, 2016 p. 497:6-16 and Ritchie Exhibit 47 MSFT_MOUSSOURIS_00002234.

[redacted][83] [redacted][84]

The data suggest the direct manager has the greatest weight in promotion decisions

114. I use the "Reports To Personnel Number" variable in the MS People data to construct the hierarchy up to seven levels. Neither data source specifically indicates which supervisor makes the most impactful decision: each level of supervisor may have varying degrees of influence on the final decision. However, one can observe the initial promotion nomination made by the direct manager, and also observe the extent to which these initial nominations are modified by others. The data show that approximately 75% of the time the initial manager's recommendations are accepted. This would suggest that initial managers have the greatest weight in promotion decisions, which makes economic sense, since they are the managers closest to the work content of the employees being considered.

115. In order to account for the impact of different supervisors, I assign a weight to each supervisor in an employee's hierarchy.[85] Since the data suggests that supervisors who work most closely with an employee likely have the most impact in a promotion decision, I adopt a functional form for the supervisor weights that decreases exponentially with subsequent

[83] Declaration of Larissa Johnson on January 25, 2016 p. 3.
[84] Ritchie Exhibit 44 MSFT_MOUSSOURIS_00004283.
[85] I construct each employee's supervisory hierarchy by using the "Reports to Personnel Number" field in the MS People Job History data, and successively applying this field upwards to construct the supervisory chain.

supervisors further up in the hierarchy.[86] I then construct a promotions one sample binomial "z-score" model that controls for supervisor, as well as other factors.

One sample binomial selection models of promotion

116. In order to apply the weights and take the timing of promotions into account more accurately, I switch at this point from probit models to Z-models. Selection pool models are probably more commonly used in statistical analysis of selection practices in employment litigation than any other statistical technique, and much has been written about their use.[87] Briefly, the approach is to construct presumed homogeneous pools with respect to the variables available for study, where employees within these pools are considered similar, except for their gender. The gender-neutral hypothesis is that selections from a given pool should be unrelated to gender, and hence for each pool, the female proportion promoted from the pool is expected to be roughly equal to the proportion of women in the pool, give or take a statistical margin of error. The "Z-model" can also be aggregated up from the underlying strata, to obtain an overall result. However, unlike the probit approach, which is inherently only aggregated, the Z-model allows one to examine the underlying strata outcomes, as well as to conduct the analysis by different time periods.

117. The essential bottom line findings of an aggregated Z-model are quite similar to a probit approach, assuming each approach takes the same variables into account. Also similar to the

[86] The weights are constructed so that the sum of the supervisor weights for each promotion equals to one.
[87] Piette, Michael J. and Paul F. White, "Approaches for Dealing with Small Sample Sizes in Employment Discrimination Litigation," *Journal of Forensic Economics* 12(1), 1999, pp. 43-56. Haan, C., E. Reardon, and A. Saad, "Employment Discrimination Litigation", chapter in *Litigation Services Handbook*, ed. by Roman Weil, et al., 1995, 2001, 2006, 2012, 2017. Connelly, Walter B., David W. Peterson, and Michael Connolly, updated by Scott Zesch. *Use of Statistics in Equal Employment Opportunity Litigation*, New York, New York: Law Journal Press, 2011.

probit approach, the Z-model uses the number of standard deviations as the test of statistical significance.

When the managerial hierarchy is taken into account, women in the Engineering profession receive 98% of expected promotions

118. The z-score model controls for promotion timing, year, review month, discipline, Stock Level, performance rating, and supervisor.[88] The table below summarizes for Engineers the promotion shortfalls and z-scores overall, and for the annual review period, the mid-year period, and for other times during the year. The model applying the control for supervisor hierarchy results in a promotions shortfall of 92. The number of standard deviations is 3.03, which is just shy of the Supreme Court's standard of within "two or three standard deviations."[89] Regardless of whether or not the result is statistically significant, it certainly is very small, and hence not practically significant. Relative to the total expected number of female promotions of 4,158, a shortfall of 92 promotions represents only 2.2%.[90] Women received 97.8% of expected promotions in the Engineering profession.

[88] This model includes more promotions than Dr. Farber's analysis, because all promotions, not just adjacent year stock level changes are counted in the analysis. Using all promotions leads to more than 17% additional total promotions being analyzed.

[89] Typically statistical significance is with reference to the two standard deviations benchmark, in spite of the Supreme Court's language in *Hazelwood Sch. Dist. v. United States*, 433 U.S. 299 (1977). One can interpret the three standard deviations upper bound as acknowledgment that with enormous sample sizes, such as in this case, a given sized disparity will be more significant than if there were fewer selections.

[90] This difference between male and female promotion selections is well below the 80% threshold the EEOC uses to flag situations that warrant a closer investigation. The threshold is not a statistical benchmark but rather one analogous to the concept of practical significance. "The agencies have adopted a rule of thumb under which they will generally consider a selection rate for any race, sex, or ethnic group which is less than four-fifths (4/5ths) or eighty percent (80%) of the selection rate for the group with the highest selection rate as a substantially different rate of selection. See Section 4D. This "4/5ths" or "80%" rule of thumb is not intended as a legal definition, but is a practical means of keeping the attention of the enforcement agencies on serious discrepancies in rates of hiring, promotion and other selection decisions." https://www.eeoc.gov/policy/docs/qanda_clarify_procedures.html

When Decision Makers are Taken Into Account, the Shortfall in Female Promotions Overall Falls Significantly

- The Female Promotion Rate is 98% of the Male Promotion Rate -
- Controls for Cycle, Fiscal Year, Review Month, Discipline, Stock Level, Performance, and Supervisor -
- Engineering Profession, 9/16/2012 to 9/1/2015 -

Promotion Category	Actual Number of Female Promotions	Expected Number of Female Promotions	Shortfall	Shortfall Percent Relative to Expected	Z-Score	P-Value
[1]	[2]	[3]	[4] = [2] - [3]	[5] = [4] / [3]	[6]	[7]
Overall	4,066	4,158	-91.96	-2.21%	-3.03	0.0024
Annual Review	[redacted]	[redacted]	[redacted]	-0.51%	-0.55	0.5834
Mid-Year				-5.43%	-2.91	0.0036
Other				-4.81%	-2.91	0.0036

119. Separately examining annual and mid-year and other promotions demonstrates that the shortfall is also reduced when adding supervisor controls for each of these groups. For annual promotions alone, the difference is [redacted] and it is not statistically significant. Women received 99.5% of expected promotions in the annual cycle.

120. Next we examine female promotion outcomes for mid-year promotions that occur during March versus those that occur during other times of the year. For March promotions, the shortfall is [redacted] out of [redacted] expected promotions, or 5.4%. For promotions at other times of the year, the shortfall is [redacted] out of [redacted] expected promotions, or 4.8%. Combining these results, if one regarded the shortfall of [redacted] during the annual review process to be effectively zero, then there is only a "significant shortfall" of [redacted] overall, which represents just 1.9% of expected female promotions.

121. It is important to emphasize that there continue to be factors which are not or cannot readily be measured, and which are thus omitted from the analysis. Some of these factors may be correlated to gender, and thus even this small shortfall in the number of promotions awarded to women may be overstated.

122. The same analysis can be applied to employees in the IT Operations profession. Overall, IT Operations profession women received 100.65% of their expected promotions. The results are not statistically significant, which is to be expected when women received 343 actual promotions relative to 341 expected promotions. In the annual review promotion cycle, IT Operations profession women received almost exactly the expected number of promotions ([redacted]). For March promotions, women received an excess of two promotions ([redacted]). For IT Operations profession employees, promotions other than annual or mid-year are [redacted] women received exactly the number expected ([redacted]).

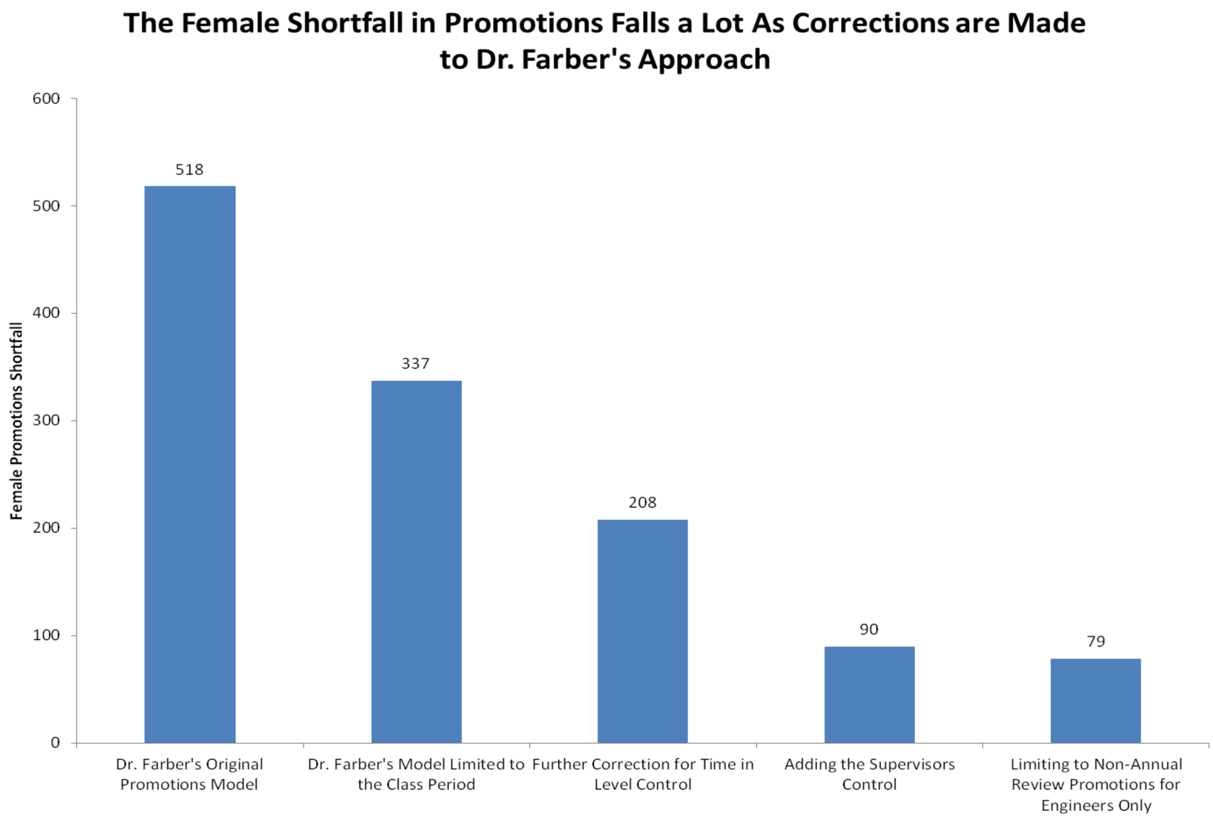
When Decision Makers are Taken Into Account, the Shortfall in Female Promotions Overall Falls Significantly

- With Supervisor Controls, the Female Promotion Rate is 101% of the Male Promotion Rate -
- Controls for Cycle, Fiscal Year, Review Month, Discipline, Stock Level, Performance, and Supervisor -
- IT Operations Profession, 9/16/2012 to 9/1/2015 -

Promotion Category	Actual Number of Female Promotions	Expected Number of Female Promotions	Shortfall	Shortfall Percent Relative to Expected	Z-Score	P-Value
[1]	[2]	[3]	[4] = [2] - [3]	[5] = [4] / [3]	[6]	[7]
Overall	343	341	2.22	0.65%	0.23	0.8148
Annual Review	[redacted]	[redacted]	[redacted]	-0.05%	-0.02	0.9861
Mid-Year	[redacted]	[redacted]	[redacted]	1.98%	0.38	0.7012
Other	[redacted]	[redacted]	[redacted]	1.84%	0.22	0.8256

123. When promotions are modeled appropriately, taking into account the variables that impact chances of selection for promotion, as well as taking into account the decision making level of the process, there is a very small overall shortfall that does not rise to the level of practical significance. Taking Engineering and IT Operations together, and regarding the shortfall in Engineering during the annual review process to be effectively zero, there is a shortfall of 1.76% (a shortfall of 79 promotions out of 4,499 expected promotions in the two professions combined). Furthermore, promotions associated with the annual review calibration/people meeting process are gender neutral. Outside of the annual promotion process, where we have the least information relevant to what determines selections for promotion, there are larger, though still very small, shortfalls in female promotions.

124. The chart below summarizes the discussion above and shows that in the end, what is at issue is a shortfall of just 79 promotions over the course of a 4 year period. I turn next to address Dr. Farber's analysis of the gender distribution across stock levels.



Dr. Farber does not include Standard Title in his promotion and Stock Level distribution analysis

125. Dr. Farber asserts that women are placed in lower Stock Levels and Career Stages than their male peers, because they are under-promoted. However, his analysis comparing Stock Level distributions by gender summarized in his Figure 3 excludes Standard Title as a control variable in his analysis of women's placement within Stock Levels. Elsewhere, Dr. Farber uses Standard Title in his pay analysis to control for the "type of work they perform."[91] As he stated at his deposition, "I control for Standard Title, which is a very detailed -- I control for discipline, which is quite detailed, and then for Standard Title, which is extremely detailed and is meant to -

[91] Report of Dr. Henry Farber, p. 15, ¶33.

- basically captures the work the individual is doing."[92] Surely to compare the Stock Level distribution by gender, one should control for the type of work they do.

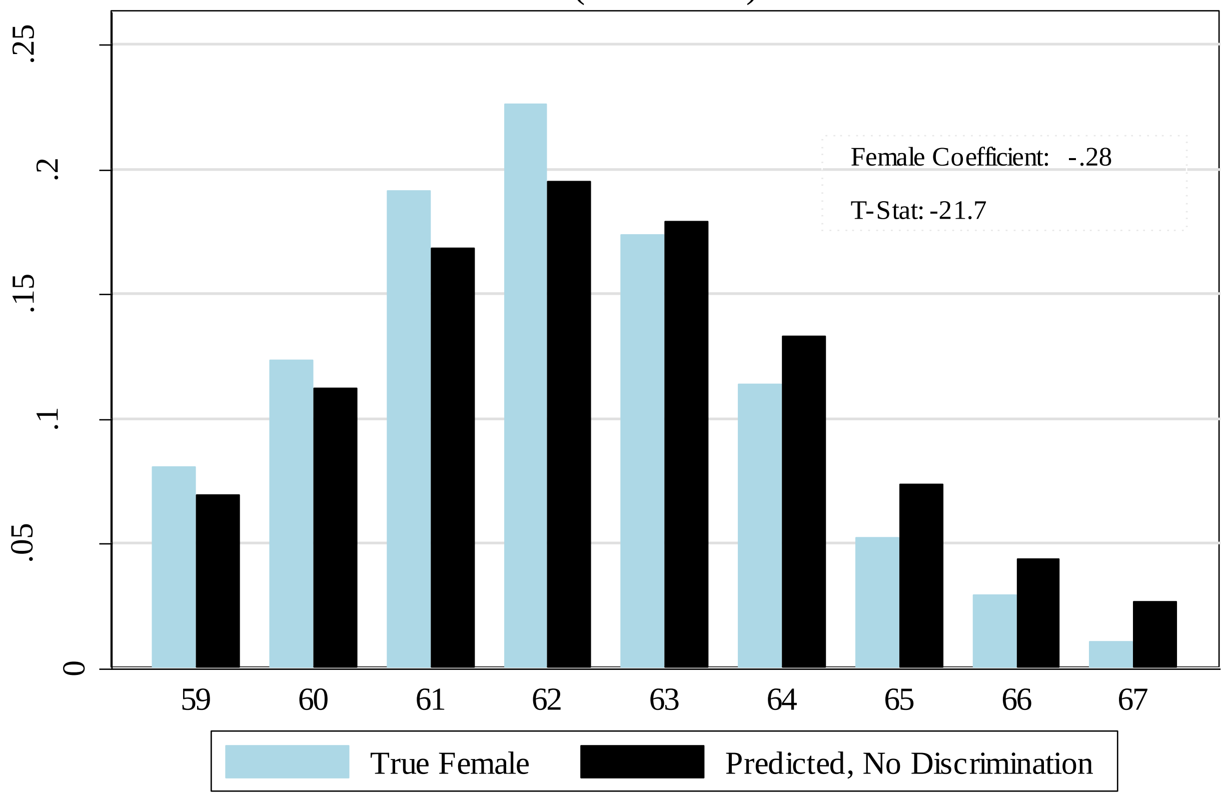
126. The results of his Stock Level analysis appears in the bottom panel of his Figure 3, which compares the actual distribution of women's Stock Levels with the distribution predicted from the results of an ordered probit analysis that controls for "each worker's tenure and tenure squared, each worker's age and age squared, the state where each employee works, each employee's PayScaleType and Discipline, the city where each employee works, performance ratings, and indicator variables for each compensation year."[93] Based on this ordered probit analysis, Dr. Farber concludes that "if women were assigned to Stock Levels in the same manner as men, there would be fewer women in the lowest levels (59–62) and more women in the highest levels (63–67). The coefficient on the female indicator variable in the ordered probit analysis is negative (-0.28) and is statistically significant."[94]

127. Dr. Farber's ordered probit model omits Standard Title, for which there is no basis, considering his use of it elsewhere. I have re-examined Dr. Farber's Stock Level distribution analysis by simply adding Standard Title to his probit regression models.

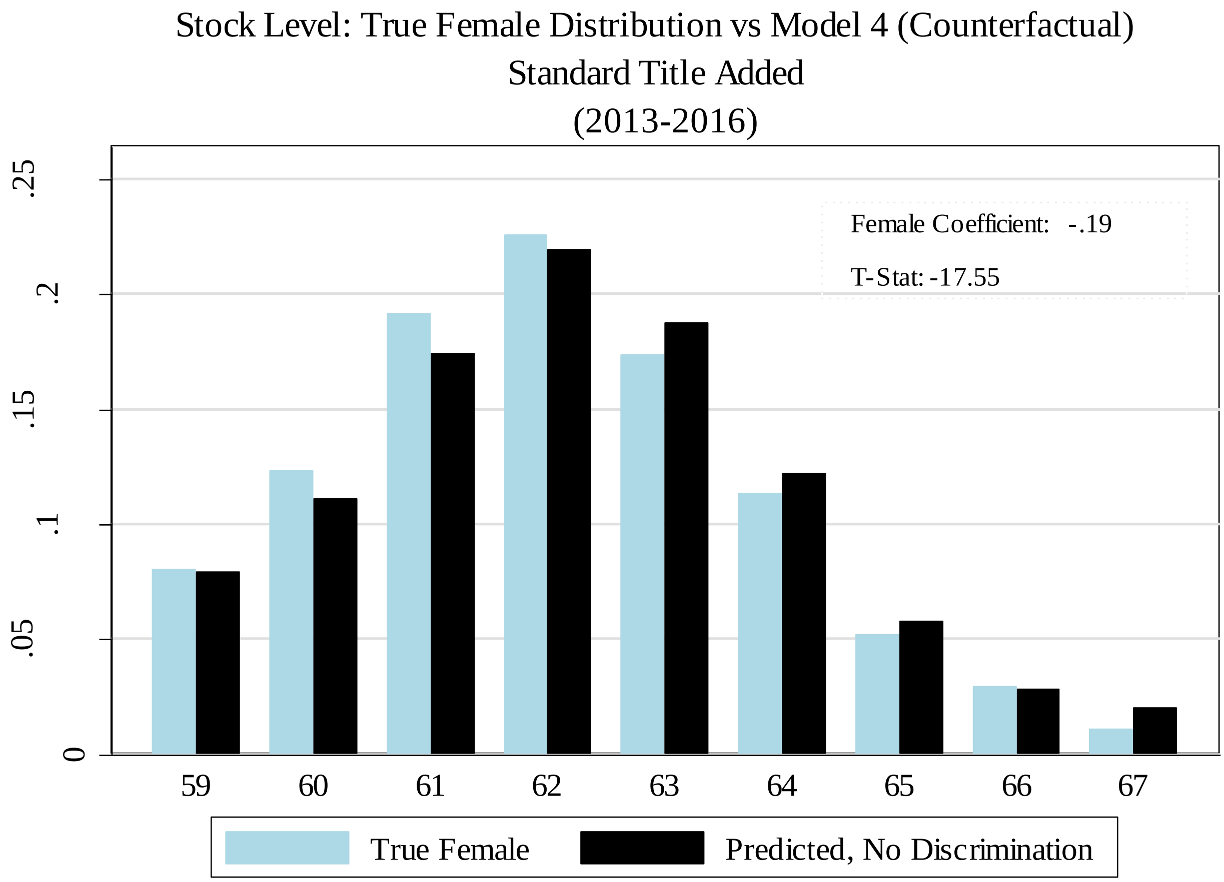
128. I first corrected Dr. Farber's analysis in Figure 1 by (1) limiting the analysis to the class period (2013-2016). The results are basically the same as those presented by Dr. Farber which included the years prior to the class period:

[92] Deposition of Dr. Henry Farber, 141:18-25.
[93] Report of Dr. Henry Farber, p. 29, fn. 53
[94] Report of Dr. Henry Farber, p. 29, ¶64.

Stock Level: True Female Distribution vs Model 4 (Counterfactual) (2013-2016)



129. Next, I added Standard Title as a control to Dr. Farber's probit model. When Standard Title is added, the estimated female coefficient drops from -0.28 to -0.19. The result is still statistically significant, but there is a large 32% change in the size of the estimated coefficient.



130. As can be seen when comparing the figures, including Standard Title as a control variable in the ordered probit analysis of Stock Level reduces the estimated distributional differences in Stock Level between men and women. This analysis does not control for any other factors, such as supervisor effect. The estimates from Dr. Farber's original model, excluding Standard Title, indicated that 7.6% of women were "misplaced" in Stock Level, while 92.4% were correctly placed. However, when Standard Title is added as a control the proportion of "misplaced" women drops to 3.8%, and the corresponding proportion of "correctly" placed women goes up to 96.2%. But Dr. Farber provides no discussion of his selection of variables for his promotion

model, and does not provide any indication of why Standard Title was not included as an explanatory variable.

Promotion velocity of new hires is the same by gender

131. Microsoft tracks velocity for employees by calculating the difference between an employee's initial and current Stock Level divided by the number of years at Microsoft.[95] To study velocity in the class period (and not promotion decisions that were made outside of the class period), I calculate velocity for employees hired during the class period. I compare their initial and current Stock Levels, and whether the rate at which men and women receive promotions is significantly different.[96] The table below shows the average velocity by gender, profession and initial-hire Stock Level. For each of these groups, I find that promotion velocity does not differ significantly between men and women. Furthermore, in some groups, women have a higher velocity on average than men. In other words, they appear to be promoted faster, although this result is not statistically significant.

[95] Promotion velocity is defined in AL5 (MSFT_MOUSSOURIS_00000036) as "LevelsAttainedAtMS divided by (MonthsAtMS / 12)".

[96] For this analysis, I exclude employees who were hired in the last fiscal year of the available data, because these individuals' histories are very short. I also restrict the analysis to the relevant period. The number of years at Microsoft is calculated as the difference between the most recent hire date and the termination date or 9/1/2016 (whichever is earlier). The MS People data has a variable called "On Hire Level," which indicates a person's initial stock level, but the field is missing for 48% of employees who were hired before 2010. Thus, I cannot construct their within-class period velocity.

The Velocity in Promotions is Not Significantly Different Between Men and Women
- Limited to Employees Who Were Hired Between 9/1/2012 and 8/31/2015 –

Profession	Stock Level at Hire	Number of Females	Number of Males	Average Velocity Females	Average Velocity Males	Difference	T-Value
[1]	[2]	[3]	[4]	[5]	[6]	[7] = [5] - [6]	[8]
Engineering	59	738	3,040	[redacted]	[redacted]	0.00	-0.02
	60	365	1,240	[redacted]	[redacted]	0.00	-0.18
	61	225	1,121	[redacted]	[redacted]	0.02	0.73
	62	146	747	[redacted]	[redacted]	-0.02	-0.81
	63	116	652	[redacted]	[redacted]	-0.03	-1.10
	64	53	332	[redacted]	[redacted]	0.06	1.69
IT Operations	59	45	200	[redacted]	[redacted]	-0.05	-1.05
	60	20	108	[redacted]	[redacted]	-0.05	-0.74
	61	43	129	[redacted]	[redacted]	0.02	0.48
	62	61	153	[redacted]	[redacted]	0.03	0.79
	63	33	97	[redacted]	[redacted]	-0.01	-0.15
	64	21	69	[redacted]	[redacted]	0.08	1.99

PAY AT MICROSOFT

132. From a labor economics perspective, in order to examine whether two groups of employees are paid differently because of their gender, the analyst seeks to account for all other explanations of an observed pay difference, including differences in job requirements, the skills needed to perform jobs, and job responsibilities. This is because as discussed above discrimination as a statistical factor is inherently unobservable in data – its possible presence or absence is only inferred, after all other observable explanations are examined. There is no "gender treatment factor" in a database – but there are (or may be) measures of job-related attributes. The labor economist must examine and consider each of these job related factors before inferring that there is a possible causal connection between gender and pay such that pay

decisions might be inferred to be motivated at least in part by gender. At issue is whether women receive lower pay for performing the same work due to their gender, not something else.

133. In Table 3 of his report, Dr. Farber presents a series of results from pay regression models that do not appropriately compare women and men doing similar work and sharing similar responsibilities for which they are compensated. He argues that because there is a gender shortfall in promotions to higher Career Stage and Stock Level categories, that these variables are inappropriate, "tainted" controls in a pay regression. This is an extreme position to hold. As noted above, his own results based on a flawed model of promotions indicate that most women are appropriately placed in Career Stages and Stock Levels, and promoted accordingly. The gender bias in promotions or in Stock Level placement he reports are small, too small to justify *entirely excluding* these measures from pay analyses. And as I show above, the promotion shortfall is very small when analyzed correctly. Thus, I will first present results including full measures for Stock Level or Career Stage. I then analyze pay using measures that "discount" the impact of Career Stage and Stock Level by an estimated "bias factor" presumed for the sake of the analysis, as taken from the promotion analysis. The idea is that excluding Career Stage and Stock Level completely is technically unsupportable, given their importance to grouping similar jobs and the small shortfall estimated by Dr. Farber, and the even smaller shortfall I find when correctly studying promotions as far as the available data permit.

134. Dr. Farber's other stated reason to exclude Stock Level from his pay models is that "There is a conceptual problem with controlling for Stock Level in a compensation regression: namely that Stock Level is a pay band. If you were to regress compensation on Stock Level, then you would simply be regressing pay on a proxy for pay, which is inappropriate."[97] As I demonstrate at length below, this characterization of Stock Level is incorrect and misleading, as

[97] Report of Dr. Henry Farber, p. 21, ¶ 47.

Dr. Farber himself implicitly acknowledges by conducting his promotions analysis by regarding advancement within Microsoft as moving to a higher Stock Level.

135. Furthermore, as in the analyses using Dr. Farber's pay models above, when I examine women's predicted pay based on their characteristics versus their actual pay, there is enormous variation in the extent to which women earn more or less than predicted, and there are numerous examples of women having the same characteristics and thus same predicted pay, yet their actual pay is quite different. It would require additional, individualized data on their skills and background to understand what is driving that variation. There are also so many different jobs, types of work, and other variations in circumstances that variations in outcomes simply abound among these putative class members.

Dr. Farber's pay regression models do not properly compare similarly situated employees

136. In Table 2 of his report, Dr. Farber presents the results of statistical tests indicating whether women and men are paid the same on average each year, with no controls for any characteristic other than gender. As he notes, the data includes all employees who were employed only in the Engineering and IT Operations professions each year and began the year in Stock Levels 59-67.[98] Nonetheless, despite these distinct differences in pay and reporting structure as well as personal characteristics such as age and education, Dr. Farber combines these groups in Table 2. His "results" are consequently not informative and should be entirely disregarded. These results are not meaningful, and as such only serve to confuse the reader who is unfamiliar with how labor economists study pay differences between groups of employees.

[98] The notes to Table 2 also indicate that employees missing tenure or age are excluded, as are employees whose annual salary equals $1 and those whose Career Stage is ATR-C, ATR-D, ATR-E, IC-0 or MA.

137. Fortunately, Dr. Farber presents additional analyses of total compensation analyses in Table 3 of his report. (Note, however, that all of these results contain data from 2010 and 2011, prior to the class period.[99]) He presents findings based on five regression models, successively adding additional control variables from one model to the next. Model 1, for example, controls only for gender, and is essentially equivalent to the approach of his Table 2. This model simply reflects the difference in average pay between women and men without accounting for any other differences (such as age, education, tenure, professional specialties and other factors). The explanatory power of this model, as expressed by adjusted R-squared in the second from the right column, is virtually zero. R-squared ranges from zero to 1, and represents the proportion (or percentage when multiplied by 100) of the variation in the dependent variable being studied, compensation, that can be explained by differences in the independent variables, which in Model 1 is only gender. In this model, gender alone accounts for under 1% (.009) of the pay differences between individuals in the sample. Model 2 adds more controls to the model: age, tenure at Microsoft, location, Pay Scale type, and year.[100] These variables taken all together explain 34% of pay variation, but only 14% of the gender pay difference observed in Model 1, since the "percent difference" in the third column from the right in Dr. Farber's table falls from -8.6% to -7.4%.[101]

138. These are not adequate control variables that similarly situate employees. The types of work these enormously variegated employees are doing vary widely. Consider that there are 278

[99] There are also 6 people (all men) in his data who are coded as Pay Scale Type "United States" but whose annual salary is not paid in US dollars: in 2013, employee 82725 was paid in UK pounds, and in 2016, 5 employees were paid in Israeli Shekels (IDs 847760, 873430, 874857, 1001650, 1002883).

[100] His use of age and months since hire at Microsoft to account for prior experience at Microsoft is problematic, given the well documented differences between men and women in terms of leaves of absence and time spent not at work. For this section, the variables are used because they appear in his models. I will return to this issue later in the report.

[101] (8.6-7.4)/8.6 = .14

different standard job titles in use during the class period, from two different professions, across 24 disciplines, for which pay ranges from under [redacted] Model 2 would predict the same pay for two 40-year old employees with 15 years at Microsoft in Redmond in 2015 under payscale "E&R". One (female) earned an annual salary of [redacted] and the other (male) earned [redacted] in annual salary.[102] Dr. Farber's Model 2 would attribute that entire 28.6% pay difference to gender. Similarly, the model would predict the same pay for two 30-year old employees with 5 years of experience at Microsoft in 2014. However, a Senior Software Development Engineer earning [redacted] and a Program Manager earning [redacted] are clearly not similarly situated.[103] Both are men, meaning that gender does not explain the 78% pay difference. Model 2 does not describe pay well even when gender does not drive differences in pay. As noted, this is evident in the low adjusted R-squared of his model: just 34% of the observed variation in earnings is explained by this model.[104]

Performance ratings do not explain any of the gender pay difference, which contradicts Plaintiffs' theory that ratings differences cause pay differences.

139. Model 3 of Dr. Farber's Table 3 is a very important model for purposes of examining the empirical basis of Plaintiffs claim in their SAC that performance measures are biased against women at Microsoft. The reason this model is useful is that the only difference between Dr. Farber's Model 2 and Model 3 is the addition of performance ratings. It is notable that this

[102] Personnel numbers 114275 and 125155.
[103] Personnel numbers 423256 and 365768.
[104] The R-squared statistic measures how closely the regression model fits the data. It ranges from 0% (explains nothing about the variation in the data) to 100% (perfect fit). In the labor economics literature on earnings, an R-squared of 30-40% is common, but those models are estimated over individuals working in different industries, occupations, and companies. Here, we are considering earnings at a single company – the R-squared should be much higher. In my experience, typical R-squared results using company level data are in the 60% to 90% range.

model fits his data much better: the adjusted R-squared now explains 51% of the observed variation in the data. Differences in performance evaluations regardless of gender matters a lot to pay – an incremental 17% is explained by this variable alone. However, while performance rating is clearly important to understanding the overall determinants of pay, his results indicate that performance rating does not affect the gender *difference* in pay. If performance measures were biased against women, including a variable for ratings in a pay regression would serve to reduce the coefficient on the gender variable, since the gendered negatively correlated performance measures would not explain and take away some of the pay differences associated with gender that are present without the inclusions of the performance measures. However, the model without performance rating estimates a -7.4% pay difference between women and men, and the model including performance rating also estimates a gender pay difference of -7.4%. The performance review process that Plaintiffs' point to as generating pay differences between women and men actually does not contribute at all to a gender difference in pay. This finding regarding pay is consistent with my two earlier analyses, first of performance evaluation, where no gender differences were found, and second, of the relationship between pay components and performance evaluation, where performance level closely relates to pay component setting.

140. In addition to my own analysis, a look at Dr. Farber's Table 4 shows why adding performance ratings to the pay regression models explains a lot about pay but nothing about the gender pay difference. Women and men receive the same ratings in most years shown in the table. The only year of statistically significant difference is 2011, which is outside of the class period, and because the differences identified are tiny, even in 2011, none of the gender pay difference is explained by including performance ratings.

Dr. Farber's regression models omit important explanatory variables, thereby treating dissimilar employees as one undifferentiated mass

141. Even after controlling for performance rating, Dr. Farber's pay regression Model 3 estimates a 7.4% pay difference between women and men. Dr. Farber's Model 3 does not distinguish between the types of jobs employees perform, or the kinds of skills and experiences employees bring to their job. By omitting statistical control variables that indicate job level, skill or responsibility, Dr. Farber attributes in this model all the observed differences in their actual pay to their gender. In addition, Dr. Farber does not take into account the different areas of the company within which employees work. For example, some employees work in Windows products, while others work on Cloud Computing projects.

Dr. Farber's pay regressions aggregate over important distinctions among female employees

142. There is a wide variety of work being compared with what amounts to a simple test of average differences in Dr. Farber's models. For example, the two technical professions are quite different. A profession is defined at Microsoft as, "A collection of multiple related disciplines with common success differentiators (competencies) and management requirements, often associated with formal education, such as Engineering, Sales, or Marketing. A profession provides a basis for a career path."[105]

143. IT Operations employees tend to earn statistically significantly less on average, despite being statistically significantly five years older on average, and the high end of their earnings range is lower (the highest earner was paid [redacted] among the Engineers).

[105] Declaration of Martin Loughlin, p. 17.

Employee Distribution Across Professions in Dr. Farber's Data During the Class Period

Profession	N	Average Total Compensation	Minimum Total Comp	Maximum Total Comp	Average Age	% Female
[1]	[2]	[3]	[4]	[5]	[6]	[7]
Engineering	124,157	[redacted]	[redacted]	[redacted]	36	16.70%
IT Operations	11,005	[redacted]	[redacted]	[redacted]	41	20.70%

144. Among those for whom there is education data, [redacted] There is very little crossover between the professions as well, on the order of 1.6% of employees over the class period.[106]

Education Distribution by Profession in Dr. Farber's Data During the Class Period

Degree	Engineering	IT Operations
[1]	[2]	[3]
Missing or Unknown	[redacted]	[redacted]
Less than a Bachelor's Degree	[redacted]	[redacted]
Bachelor's Degree	[redacted]	[redacted]
Master's Degree or More	[redacted]	[redacted]
Total	[redacted]	[redacted]

145. Employee Stock Levels (similar to job grades, and used to award stock grants[107]) are statistically significantly different between the two professions. Considering that compensation is determined within a profession, and that professions map to levels differently, this is not surprising.[108]

[106] This excludes 2016 when Microsoft reorganized IT Operations, reducing its size dramatically and moving some employees into Engineering.
[107] Declaration of Martin Loughlin, p. 19.
[108] "It is the combination of the following that determines compensation levels: what you do (profession

Stock Level Distribution by Profession in Dr. Farber's Data
During the Class Period

Stock Level	Engineering (%)	IT Operations (%)
[1]	[2]	[3]
59	7.07	6.50
60	10.41	8.21
61	15.72	16.18
62	18.72	25.28
63	18.15	19.67
64	13.97	14.75
65	8.20	5.22
66	4.86	2.78
67	2.91	1.41
Total	100.00	100.00

Chi Square Test : Pr = 0.0000

146. Nonetheless, despite these distinct differences in pay, promotion and reporting structure as well as in personal characteristics of the two employee workforces, Dr. Farber combines these groups into aggregated analyses.[109] Even within those professions, however, there are distinct differences in the types of work being performed. The next level in the job classification system used by Microsoft is discipline. The chart below shows that average total compensation in the Engineering General Management discipline and the IT Operations Leadership discipline is more than double the total compensation in the Art discipline, Audio discipline, or IT Service Operations, among others. This dwarfs any difference by gender, and is surely a function of characteristics of the job and work content. These differences are obscured by the aggregated way Dr. Farber estimates his models.

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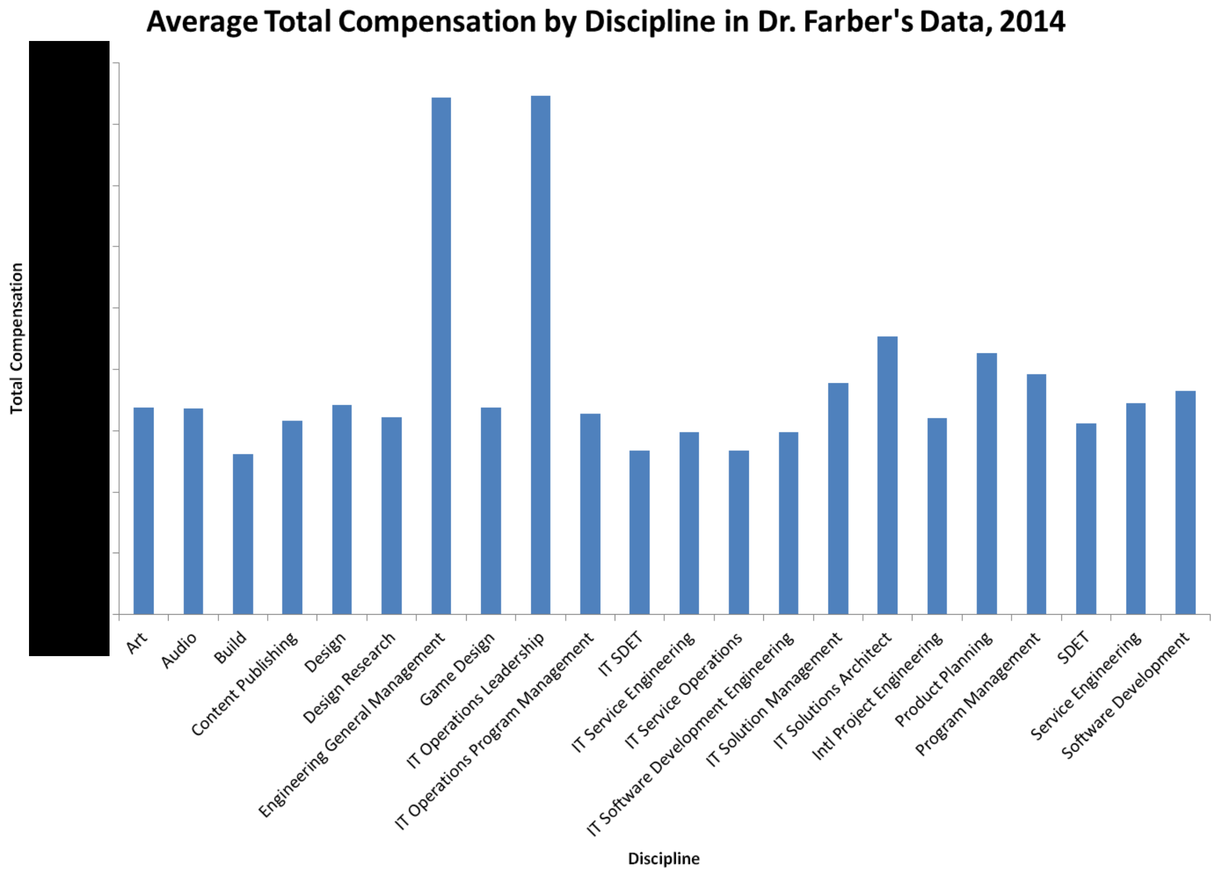
and discipline), what scale and complexity (career stage), and where you do it (location).” Career Stage to Level Mapping, MSFT_MOUSSOURIS_00001997.

[109] The Chow statistical test rejects combining these professions into one pay model.



147. Model 4 in Dr. Farber's Table 3 adds profession and discipline as control variables. The gender pay difference drops from -7.4% to -6.3%, indicating that gender differences in profession and discipline explain almost 15% of the observed difference from his Model 3. This illustrates a broader point about what is and is not included in Dr. Farber's models. Omitted variables *that are correlated* with included variables of interest (i.e., gender) will lead an analyst to attribute too much or too little impact to the included variables. Women and men differ in their distribution across disciplines, and this accounted for almost 15% of Dr. Farber's estimated pay difference as reported in his Model 3. In other words, if one stopped at Model 3, then clearly there is an upward bias built into the 7.4% gender difference reported in Model 3, which is only discovered when discipline is added to the model. Statisticians and econometricians call the failure to include excluded variables that are correlated with included variables of interest

"omitted variable bias."[110] In the human capital literature, a considerable amount of research has focused on the biases caused by omitting important statistical determinants of earnings when conducting studies designed to measure the impact on earnings of other specific variables of interest.[111] It is notable that inserting discipline does not increase R-squared in Dr. Farber's analysis.

148. Moving to Dr. Farber's Model 5, he adds a control for what Microsoft calls "Standard Title." There are 278 Standard Titles present in the data analyzed, of which many have virtually no occupants. These Titles for the most part appear to be akin to occupations, as opposed to jobs sharing the application of similar skills, and sharing similar responsibilities. I will describe this in greater detail in a moment, but when Dr. Farber inserts Standard Title into his Model 4 to produce Model 5, there is a large impact. First, the R-squared increases significantly, from 55% to 79%. Clearly Standard Title is highly related to the pay differences observed among Microsoft employees regardless of gender. Second, the percent difference in female pay drops by more than half: from 6.3% to 2.8%.

[110] The principal of omitted variable bias can be demonstrated with the following example. Suppose a company wanted to estimate the impact of different types of fertilizer on crop yield. They collect data on yield and the type of fertilizer applied. There are two types of fertilizer – A and B. The company estimates the statistical relationship between the type of fertilizer applied and crop yield by using a statistical model that relates yield to type of fertilizer applied. They conclude that fertilizer A has a greater impact on yield than fertilizer B. However, suppose it turns out that for farming plots receiving fertilizer type A, greater rainfall occurred. Rainfall was omitted from the statistical analysis. Would the company be correct to infer that fertilizer A was most effective? Clearly not. If rainfall was measured and included in the analysis, it may be that fertilizer B was more effective at increasing yield, holding constant other factors, such as rainfall. Thus, the analysis that omits rainfall would produce a biased finding, in that fertilizer A was incorrectly concluded to have the greater impact on yield. Instead, in that analysis, all of the observed increases in yield were attributed to fertilizer, when in fact some of the increases in yield were due to rainfall. See for example, Greene, W. (1993) *Econometric Analysis*, 2nd Edition, NY: Macmillan Publishing Company, pp. 245-248 or any basic econometrics book.

[111] Mincer, J. (1974) *Schooling, Experience and Earnings*, New York: National Bureau of Economic Research. Griliches, Z. (1977) "Estimating the Returns to Schooling: Some Econometric Problems," *Econometrica*, 45:1-22. Willis, R. (1986) "Wage Determinants: A Survey and Reinterpretation of Human Capital Earnings Functions," Chapter 10, *Handbook of Labor Economics, Volume 1*, Edited by O. Ashenfelter and R. Layard. Elsevier Science Publishers BV.

149. At his deposition, when asked about why he chose to use Standard Title and not the other two variables associated with the level of work performed by employees at Microsoft, he repeatedly stated that his goal was to compare employees doing similar work and at similar levels of skill and proficiency, and claimed that Standard Title was an “extremely detailed” measure for these purposes. He testified at deposition, “As I've said, I control for standard title, which is a very detailed -- I control for discipline, which is quite detailed, and then for standard title, which is extremely detailed and is meant to -- you know, it basically captures the work the individual is doing.”[112] He further claimed that he did not even consider either Career Stage or Stock Level, which are the other two measures, since once he examined Standard Title, it had all the features he would want in a control variable for purposes of distinguishing between employees regarding their productive attributes while on the job at Microsoft. As I will next show, it does nothing of the sort, and Dr. Farber has failed in his Model 5 to conduct an analysis where employees are compared in as much as an “apples to apples” manner, excepting gender, as is possible with the data provided.

Career Stage is a necessary (though not sufficient) factor to group similarly situated employees in 2016

150. According to Microsoft, Career Stage reflects “the degree of scope and impact of a role,”[113] and it “defines levels of mastery, ranging from entry-level to industry-wide expertise,”[114] and is “used to benchmark pay externally.”[115] Career Stages are related to Standard Title and discipline, but not determinative, particularly in later years. In a pay

[112] Deposition of Dr. Henry Farber, 141:18-25.
[113] “Career Stage to Level Mapping,” MSFT_MOUSSOURIS_00001997
[114] “How jobs are organized,” MSFT_MOUSSOURIS_00002378, p. 21.
[115] MSFT_MOUSSOURIS_00058126, p. 10

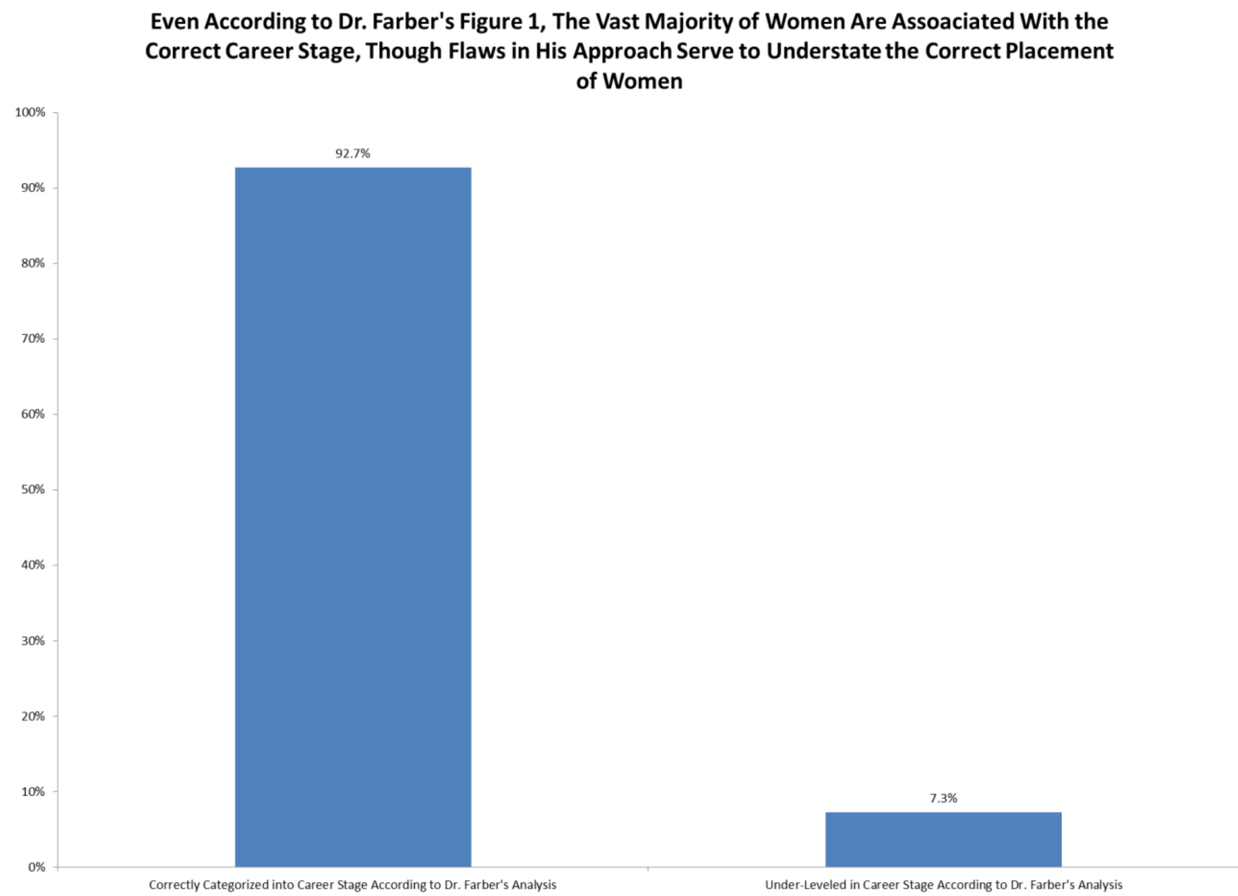
regression designed to compare similarly situated employees with respect to their skills and responsibility, Career Stage by its definition indicates the level of mastery of the work and should be included. Dr. Farber chooses not to include this factor in his models because he claims that his results show that Career Stage is "tainted" by discrimination in that women are less likely than predicted by his model to be in the higher level Career Stages. He claimed that he decided this prior to even knowing the outcomes of his promotion analysis.[116] Dr. Farber also testified that he believed controlling for Standard Title meant that Career Stage was irrelevant.[117]

151. As noted above, when I examine Dr. Farber's statistical program and the numbers underlying Figures 1 and 2 of his report, I find that the difference between the expected distribution of women across Career Stage and the actual distribution is not large. Only 7.3% of women are in a Career Stage lower than his (flawed) model predicts.[118] In other words, 92.7% of women are in the appropriate Career Stage according to his analysis. That 7.3% are supposedly under-leveled is hardly extensive enough to justify *entirely* excluding Career Stage from the analysis as a control variable.

[116] When asked if the results of his promotion analysis informed his pay analysis, he testified, "No. In fact, temporally, I conducted the compensation analysis before the advancement analysis." Deposition of Dr. Henry Farber, 226:23-25.

[117] He testified, "As I said, the version of the model with standard title essentially subsumes career stage as a subcategory, and since the titles differ within career stage, there are lots of different titles in any particular career stage, that accounts for the differences." Deposition of Dr. Henry Farber, 144:15-21.

[118] This would equal 7.1% if his analysis had been restricted to just the class period. In his Figure 2, he repeats the exercise for 2014-2016; his numbers indicate that 6.8% of women are under-leveled. Also, I showed above that Dr. Farber omitted Standard Title from his probit models underlying his Figures 1 and 2, which when resolved, indicates only 3.8% of women are potentially mis-leveled.



152. There is also another reason Dr. Farber should have considered the use of Career Stage in his regression models. As Dr. Farber notes, Standard Titles tend to track Career Stage and Discipline. However, in 2015-16, this was no longer true. Standard Titles were consolidated and in particular, software engineers at all levels were combined into a single very large aggregated title. Consider the table below. All five employees are Software Engineers in 2016, and all had been at Microsoft approximately [redacted]. Under Dr. Farber's model, all five are "similarly situated." And yet their total compensation ranges from approximately [redacted]. Dr. Farber's model cannot explain why their earnings are so different, even among the four who are men. Surely that difference is not driven by gender. Also, the average compensation for the four men is [redacted] Dr. Farber's model would attribute the 29% average

difference in pay between the one woman and the average for the men to discrimination, despite the fact that discrimination cannot explain why men in the same Standard Title, with similar tenures at Microsoft and working in the same location range have earnings ranging from just under [redacted]

Four Employees in 2016 for Whom Dr. Farber's Model Would Predict the Same Pay:
All in the Engineering Profession, Software Engineering Discipline, with the Software Engineer Standard Title in Redmond WA

[1] Age	[2] Months at MS	[3] Annual Salary	[4] Total Compensation	[5] Pay Scale	[6] Reward Outcome	[7] Gender
43	123	[redacted]	[redacted]	E&R	4	Male
43	118			E&R	4	Female
43	121			E&R	4	Male
43	119			E&R	4	Male
43	121			E&R	4	Male

153. It appears that starting in about 2015, Microsoft began consolidating Standard Titles. For example, depending on the year, 47% to 62% of all employees in Dr. Farber's file have the word "Software" in their title. The table below shows that in 2016, almost all of them were grouped into one Standard Title: "Software Engineer." Their total compensation ranges from [redacted] in 2016, a span so wide as to make obvious that these "jobs" are not comparable in scope or complexity despite the shared Standard Title.[119] This means that Dr. Farber's control for Standard Title in 2016 does not group similarly situated employees.

[119] To take a similar situation, I'm aware of companies in which job titles were designated only by the scientific discipline of the employee. "Engineer," "Mathematician," "Physicist," "Biologist," etc. These job titles never changed. Hence a fresh Ph.D. Physicist shares a job title with the leader of the entire large organization, who might earn over 10 times what the entry level employee earned.

In 2016, Standard Titles Were Consolidated for Software Engineers

Standard Title includes "Software"	Number of Employees			
Year	**2013**	**2014**	**2015**	**2016**
[1]	[2]	[3]	[4]	[5]
Director, IT Software Dev Eng	2			
IT Enterprise Software Architect		1	5	
IT Senior Software Dev Engineer, Test	5			
IT Software Development Engineer, Test	4			
IT Software Development Engineer, Test 2	11			
Lead Software Development Eng in Test	1,120			
Lead Software Development Engineer	1,427			
Manager, IT Software Dev Eng	8			
Partner Software Development Engineer			2	
Principal Software Development Engineer	782	761	886	99
Senior Software Development Engineer	3,116	3,320	3,712	410
Software Architect	92	56	60	14
Software Development Engineer	2,205	2,515	2,240	236
Software Development Engineer 2	4,090	4,348	4,466	359
Software Development Engineer in Test	2,471	2,017	1,322	19
Software Development Engineer in Test 2	3,475	3,170	2,598	35
Software Engineer			**661**	**16,589**
Software Engineering Lead			3	1,463
Software Engineering Manager			9	968
Software Test Engineer	6		2	

154. If Dr. Farber had been aware of the major consolidation in software engineer that took place in 2015-2016, he might have instead used Career Stage, at least for those two years. When Career Stage is added to Dr. Farber's Model 5, it largely does not affect the estimated gender pay difference of Model 5 in 2013-2014 because of the way it relates to Standard Title. In 2015-2016, though, as Microsoft began changing the relationship of title and Career Stage, the effect of adding Career Stage to the model to account for title consolidation among half the purported class is dramatic. The next table disaggregates Dr. Farber's Model 5 results by year (and also

restricts the data to the class period).[120] Column 2 shows that the gender difference in pay estimated by Dr. Farber's original Model 5 is constant in 2013-2014, rises somewhat in 2015 and more than doubles in 2016. This is because in 2016 especially his control for Standard Title is not useful in separating employees with similar scope and responsibilities -- virtually half of all employees in the data share a single "Standard Title."

Dr. Farber's Model 5 Does Not Account for the Consolidation of Standard Titles During the Class Period

Year	**Percent Pay Difference Using Farber Model 5 <u>NO</u> Career Stage Control**	**Percent Pay Difference Using Farber Model 5 <u>Applying</u> Career Stage Control**
[1]	[2]	[3]
2013	-1.9%	-1.9%
2014	-1.9%	-1.6%
2015	**-2.2%**	**-1.4%**
2016	**-4.5%**	**-2.0%**
All Years	**-2.8%**	**-1.8%**

155. However, column 3 shows that simply adding a control for Career Stage brings his 2015 and 2016 results more in line with the other years, *and* reduces his overall estimate from a 2.8% gender pay difference to a 1.8% pay difference. (Note that the added control variable does not have much impact in 2013-2014 when Standard Titles and Career Stage were more closely aligned).

156. This is not to say that his model including Standard Title, even augmented by the inclusion of Career Stage, adequately similarly situates employees. I turn next to a consideration of another job control variable available in the data, and which Dr. Farber also rejected – Stock Level.

[120] To produce this table, I simply ran Dr. Farber's Model 5, with Standard Title, and then added Career Stage to the model, separately by year for both.

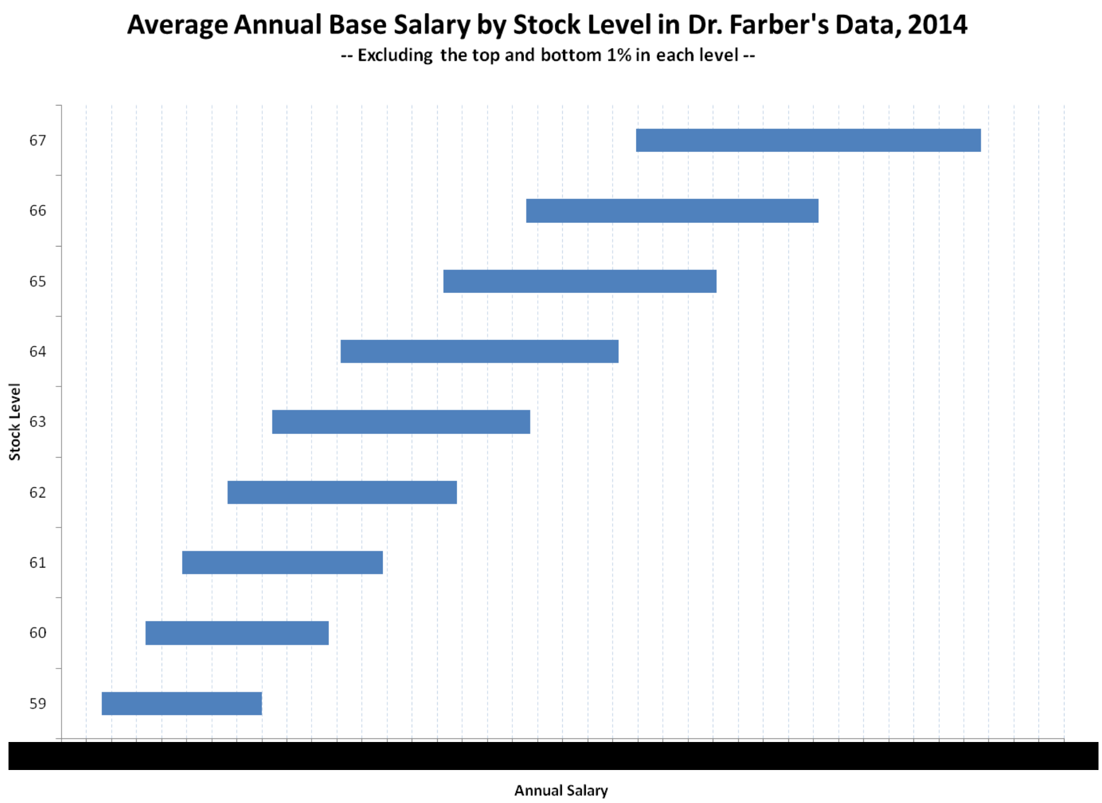
<u>*Stock Level is more than simply a "pay band"*</u>

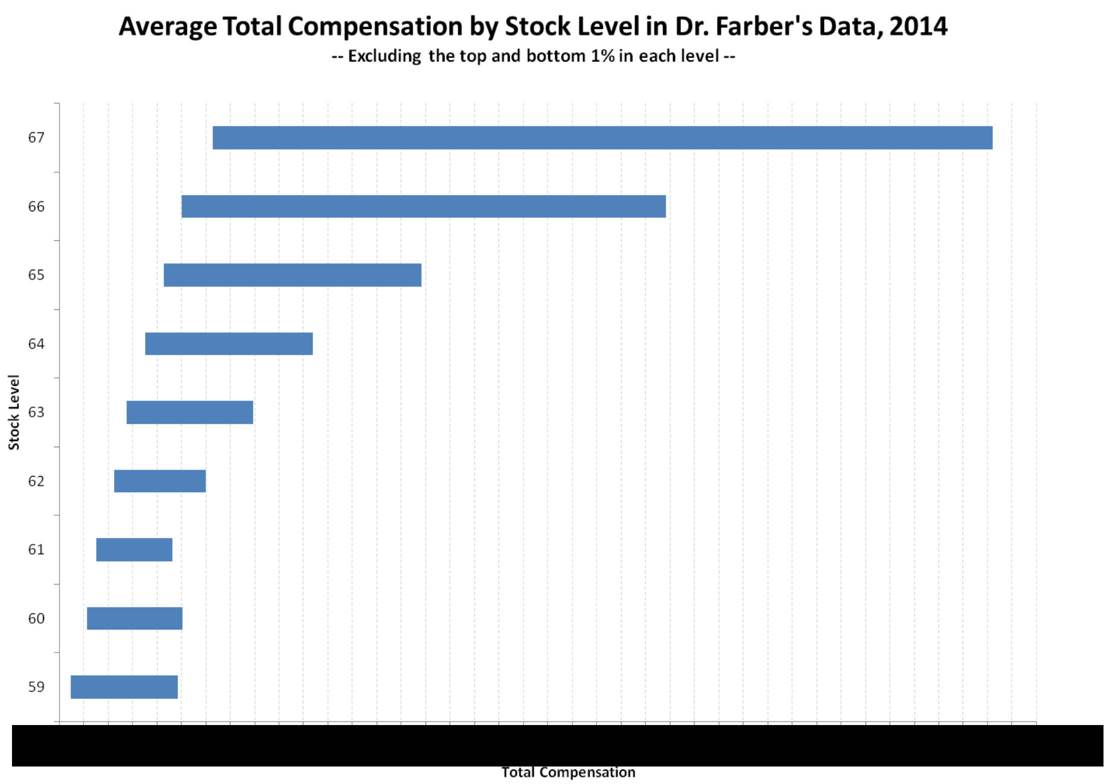
157. Dr. Farber states that he excluded Stock Level from his regression model because he claims they are simply pay bands.[121] Dr. Farber also testified at his deposition that he believed Stock Level was actually not relevant to measure skill and responsibility.[122] As noted, this does not square with his analysis of promotions: movement from one Stock Level to the next is considered by Microsoft to be a promotion, meaning a substantive change in the level of skill and responsibility, and he models this progression as a promotion.

158. Dr. Farber also stated at his deposition that perhaps Microsoft would increase an employee's Stock Level just to be able to pay them more. Aside from the loose economic logic here, it is certainly possible at Microsoft to award quite significant pay raises without promoting someone, as the range of compensation within a Stock Level is quite wide. In general, the maximum base salary in the data is about 40% higher than the minimum within a Stock Level, and the maximum total compensation is about 133% higher than the minimum within a Stock Level. This is shown in the charts below.[123] The pay ranges also overlap – it is entirely possible for a level 62 employee to earn more than a level 63, for example. So clearly, Stock Levels are not pay bands, and even if they are, they are enormously wide relative to the very small differences in pay identified by even Dr. Farber's pay models. In fact, Stock Levels are essentially hierarchical levels, indicating successively more complex work, named in a manner such that they can be conveniently used across a large and complex company. Many large companies utilize similar structures. As I will demonstrate below, what is important is that Stock Levels are created to group together employees performing work that is similar in its complexity

[121] Report of Dr. Henry Farber, page 21, ¶ 47.
[122] Deposition of Dr. Henry Farber, 104:22-25; 110:11-20; 111:11-16; 230:23-24.
[123] See also for example, the salary ranges by Stock Level for Software Development, SDET, and Software Engineer positions in Redmond, WA in MSFT_MOUSSOURIS_00308266.

and scope of responsibility, even if it differs in its specific content across the many areas of the company.





159. Standard Titles also can span several Stock Levels in a given year. For example, Software Development Engineers in Dr. Farber's data for 2013 span seven Stock Levels, as shown in the table below. Though Standard Title helps in similarly situating employees in terms of the general and very broad nature of the work they do, the level of responsibility and skill required is not adequately addressed by Standard Title alone.

Software Development Engineers in Dr. Farber's Data, 2013

Stock Level	N	Average Base Salary	Average Total Compensation
[1]	[2]	[3]	[4]
59	1,002	[redacted]	[redacted]
60	1,096	[redacted]	[redacted]
61	73	[redacted]	[redacted]
62	18	[redacted]	[redacted]
63	12	[redacted]	[redacted]
64	2	[redacted]	[redacted]
65	2	[redacted]	[redacted]

160. As noted, if Stock Levels were mere pay bands, movement from one to another would not be considered a promotion. Clearly, the levels are associated with pay ranges wide enough to accommodate wide flexibility in pay such that excellent work can be rewarded without changing Stock Level. According to Microsoft documentation, "A promotion is an increase in level, and usually with a promotion [pay] increase % as a result of increased job responsibilities and contributions or a new job at a higher level that is sufficiently greater in size, scope and impact."[124]

161. This recognition of increased scope and impact is evident in how promotions are described in the justification commentary system that accompanies promotions.[125] For example, Employee 310417 is a Design Researcher [redacted] Her justification entry read:

[redacted]

162. Clearly, her move from one level to the next required a strong signal that she would succeed at the next level -- by already demonstrating advanced skills in delivering high quality

[124] Promotions Overview MSFT_MOUSSOURIS_00004281. The word "pay" inserted for clarity. Emphasis added.

[125] There are thousands of promotion justification commentary observations in the data produced. Most, though not all, promotions have promotion justification information.

work relevant across teams and the ability to attract cooperative work across teams as well. Similarly, Employee 474370 is a Software Development Engineer 2 [redacted] His justification, like hers above, shows how employees must demonstrate they will be able to succeed at the next level before they are promoted, in essence by already performing at that higher level of skill and proficiency:[126]

[redacted]

163. This is a consistent theme in the promotion justifications. Employee 691525 is a Data and Applied Scientist [redacted] His justification read:

[redacted]

[126] This is typical of how promotions work in many if not most organizations: Companies typically do not promote employees until they observe an employee's ability to succeed at the higher level, by actually performing at that level for some period of time.

164. There are many such examples, including Employee 35721, a Software Development Engineer [redacted] whose justification included:

[redacted]

165. Employee 209164 is a Program Manager 2 [redacted]

[redacted]

166. It is clear from the Microsoft materials that Stock Levels group employees by scope and complexity and responsibility and should be included in the pay regressions to compare similarly situated employees. As noted previously from his deposition testimony, Dr. Farber acknowledges the importance of controlling for the specific nature of the work as well as the proficiency level at which it is done – i.e., "the work the individual is doing."[127] Such a statement implies both a type of work (software engineering, art design, etc.) as well as the scope or complexity of the work performed per unit of time, i.e., its level of proficiency. Standard Title does not capture all aspects of the work being done, but Standard Title in combination with Stock Level captures both the "category" of work and the level of skill or proficiency of the work. "When we assign Stock Level to employees, we look at their scope of responsibilities."[128]

167. I start by adding Stock Level to Dr. Farber's Model 5, but I perform the analysis separately for the Engineering and IT Operations professions for the reasons explained above. In the IT Operations profession, the estimated percent difference in female pay is 0.4%, and is neither statistically nor practically significant. In the Engineering profession, when Stock Level

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[127] Deposition of Dr. Henry Farber, 141:18-25.
[128] OFCCP statement submitted by John Ritchie, December 16, 2014. MSFT_MOUSSOURIS_00308280.

alone is added to the controls, it shows that the estimated pay difference between women and men is 0.9%. This, while statistically significant (due to the enormous number of data points in the analysis – almost [redacted]), is not practically significant. I alluded to this notion above. The distinction between practical and statistical significance is discussed in the Reference Manual on Scientific Evidence, in a section written by the well-known economist Professor Daniel Rubenfeld: "Practical significance means that the magnitude of the effect being studied is not *de minimis*—it is sufficiently important substantively for the court to be concerned. For example, if the average wage rate is $10.00 per hour, a wage differential between men and women of $0.10 per hour is likely to be deemed practically insignificant because the differential represents only 1% ($0.10/$10.00) of the average wage rate."[129] There is also a sizeable statistics and econometrics literature on the issue of "practical significance."[130] Indeed, Dr. Farber has used this concept in his own academic research: "As to the <u>practical significance</u> of this positive effect, it is actually quite small. The point estimate of .09 suggests that if the unemployment rate doubles from 4 percent to 8 percent union negotiated wage changes will increase by only .36 percentage points."[131] This is in contrast to his deposition testimony in which he claimed not to be familiar with the idea.[132] The table summarizing the results of adding Stock Level alone to Dr. Farber's Model 5 analysis is below. Note the sizable increase in the R-squared figures: from

[129] Daniel Rubenfeld, "Reference Guide on Multiple Regression," *Reference Manual on Scientific Evidence: Third Edition*, page 318. Emphasis added.

[130] See McCloskey, Donald N., "The Loss Function Has Been Mislaid: The Rhetoric of Significance Tests," *American Economic Review Papers and Proceedings*, May 1985, pp. 201-205. Also see Leamer, Edward, *Specification Searches: Ad Hoc Inferences with Non-Experimental Data*, New York, Wiley, 1978. Also see Piette, Michael J. and Paul F. White, "Approaches for Dealing with Small Sample Sizes in Employment Discrimination Litigation," *Journal of Forensic Economics* 12(1), 1999, pp. 43-56.

[131] Farber, Henry, "Union Wages and the Minimum Wage," MIT Econ Dept Working Paper No. 278, Feb. 1981, p. 14. Emphasis added. Published in Report of the Minimum Wage Study Commission. Vol. VI, 105-134.

[132] Deposition of Dr. Henry Farber, 277:11-14. "Are you familiar with the concept of practical significance? A: I can guess what it means, but, no, I'm not familiar with it."

.78 in Dr. Farber's Model 5 to .94 in the case of the IT Operations profession and .91 in the case of engineers.

Pay Differences By Profession in the Class Period,
Farber Model 5, Adding Only Control for Stock Level

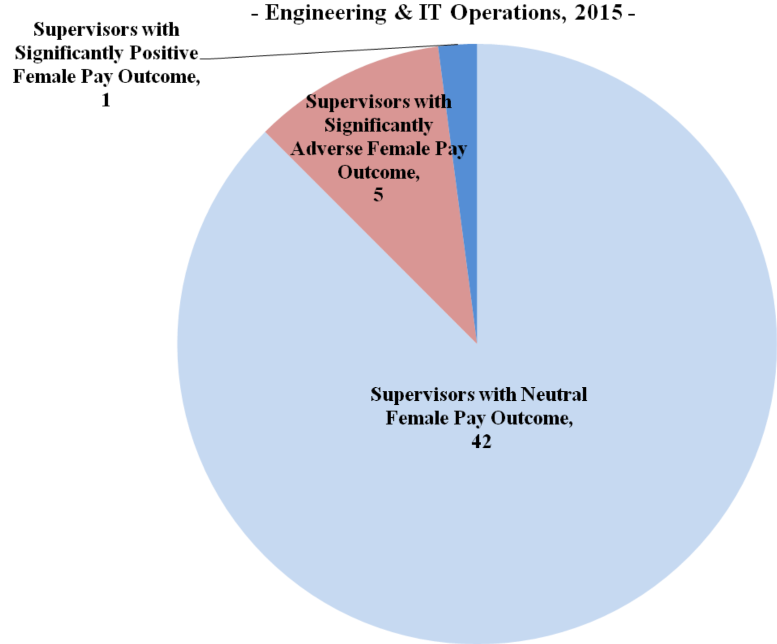
Year	Female Coefficient	t-Statistic	P-Value	Percent Difference	Adjusted R^2	Employee Years
[1]	[2]	[3]	[4]	[5]	[6]	[7]
Engineering: All Class Years	-0.009	-9.98	< 0.05	-0.9%	0.908	[redacted]
IT Operations: All Class Years	-0.004	-1.53	0.13	-0.4%	0.941	

168. This analysis can also be examined by supervisor. The pie chart below presents for 2015 the number of supervisors for whom the female coefficient was statistically significantly negative, statistically significantly positive, or not statistically significant. Only five out of the 48 Level 2 supervisors for whom statistical significance could be computed showed a statistically significant difference in pay.[133] The results are similar when I examine Level 3 supervisors.[134] My results for 2016 are similar, and can be found in Appendix 1. These findings are inconsistent with a common causal force leading to pay differences for members of the putative class.

[133] The analysis is restricted to 48 out of 77 supervisors for whom the female coefficient and T-statistic can be calculated. Nonetheless, 99.1% of women are included. Of them, 84.1% work under supervisors with neutral or significantly positive female pay outcomes.
[134] Analysis is restricted to 231 out of 446 supervisors for whom the female coefficient and T-statistic can be calculated which accounts for 95.7% of women. 93.6% of women are under supervisors with neutral or significantly positive female pay outcomes.

Level 2 Supervisors: Pay Outcomes for Women (Farber Model 5 with Stock Level)

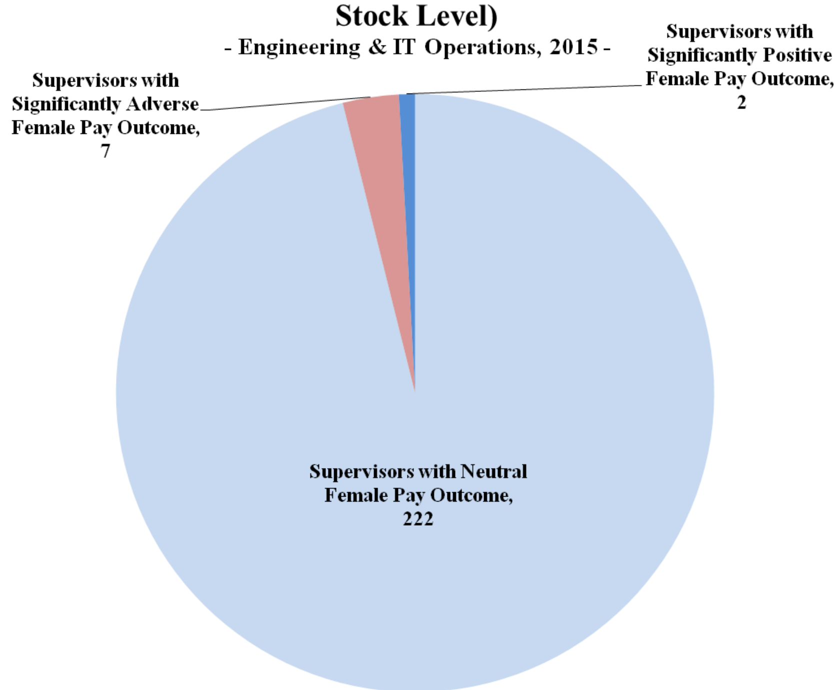
- Engineering & IT Operations, 2015 -



Note: Dr. Farber's pay Model 5 with Stock Level controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, Standard Title, and Stock Level. Analysis is limited to 48 out of 77 supervisors for whom the female coefficient and T-statistic can be calculated which accounts for 99% of women. 84% of women are under supervisors with neutral or significantly positive female pay outcome. 90% of women work in groups of 300 or more.

Level 3 Supervisors: Pay Outcomes for Women (Farber Model 5 with Stock Level)

- Engineering & IT Operations, 2015 -



Note: Dr. Farber's pay Model 5 with Stock Level controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, Standard Title, and Stock Level. Analysis is limited to 231 out of 446 supervisors for whom the female coefficient and T-statistic can be calculated which accounts for 96% of women. 94% of women are under supervisors with neutral or significantly positive female pay outcome. 38% of women work in groups of 300 or more.

<u>Taking at face value Dr. Farber's claim that Stock Level is "tainted," a method is applied to reallocate Stock Levels between men and women to remove promotion shortfalls</u>

169. Dr. Farber's compensation model (Model 5, which controls for year, gender, age (and its square), tenure at Microsoft (and its square), state, city, Discipline, Pay Scale Type, performance, and Standard Title) results in a pay difference between men and women of -2.8%. When Stock Level is added to the model as a control variable the difference drops to -0.9%. As noted, Dr. Farber's model does not control for Stock Level, as he claims that Stock Level is a "tainted" variable. However, if Stock Levels were allocated "fairly" between men and women, such that there would be no shortfall in Stock Level advancement, then Stock Level would be purged of "taint."

170. I start by accepting at face value the results of Dr. Farber's Stock Level advancement model adjusted only by a focus on the class period alone, to run a simulation model in which advancements are "re-allocated" from women to men in order to eliminate Dr. Farber's estimated female shortfall. Recall this shortfall was 337. Within Microsoft, assuming that the total number of promotions is fixed, the "under-promotion" of women can be reconciled by reversing some of the promotions men received and instead granting them to women. Operationally, in order to "reallocate" a promotion from a given Stock Level I randomly select both a male-year in which a promotion occurred and a female-year in which a promotion did not. For example, for advancements from level 59 to 60 I would randomly select a man who was promoted from 59 to 60 and "reverse" that promotion so he remains a 59, and also randomly select a woman at level 59 who was not promoted, and "reallocate" the male promotion to the woman advancing her to level 60. However, I do not increase the woman's pay or decrease the man's pay. Once a particular promotion is "reallocated," I adjust the data in subsequent years to reflect the

reallocation.[135] Another way to think about this "reallocation" is that I have simulated a "but for" world in which women are not under-promoted using Dr. Farber's model and data.

171. For the class period, Dr. Farber's probit model calculates a shortfall in the actual number of women promoted as compared to the expected. For movements from Stock Level 59 to Stock Level 60 he finds that there should have been 680 women promoted (instead of 679), and from Stock Level 60 to Stock Level 61 there should have been 882 women promoted (instead of 841 actual), and he performs a similar calculation for the other levels.[136] As discussed above, I then randomly picked one male-year with a promotion from Stock Level 59 to 60 to change his Stock Level back to 59, and one female-year that remained at Stock Level 59 to change her Stock Level to 60, again with no adjustments to their pay. By the same method, I reallocated 41 promotions for Stock Level 60 to 61, 50 promotions for Stock Level 61 to 62, 151 promotions for Stock Level 62 to 63, and 35 promotions for Stock Level 64 to 65, allocating the entire shortfall of all 337 promotions across levels 59-64 from men to women.

172. These new "reallocated" (or "but-for") Stock Levels are now "untainted," since they reflect no female shortfall. I then run the total compensation analysis (based on Dr. Farber's Model 5) with the addition of the "but-for" Stock Level as a control variable. I repeated this process of randomly reallocating promotions and running the pay regression model 50 times. The table below shows in row 3 that across the 50 iterations of the model, the average difference between male and female compensation after reallocating 337 promotions is -1.3%.

[135] In other words, I also negate the male advancement in future years, and I carry forward the female advancement. For example, if the male promotion from 59 to 60 occurred in 2013, I maintain the man's level at 59 in 2014 and 2015. The promotion would be reallocated to a woman in 2013, and she would keep the promotion going forward. If the data showed a subsequent promotion, that would be added on top of the reallocated promotion. For example, if the woman actually was promoted from 59 to 60 in 2015, I assume she receives the re-allocated promotion in 2013 and another promotion (to 61) in 2015.

[136] From Stock Level 61 to Stock Level 62 there should have been 1,089 women promoted instead of 1,039, from Stock Level 62 to 63: 1,001 instead of 850, from Stock Level 63 to Stock Level 64: 635 instead of 576, and from Stock Level 64 to Stock Level 65: 330 instead of 295.

173. Including Stock Level with no adjustment in the distribution of stock levels between men and women reduces the pay difference found by applying Dr. Farber's model from 2.8% to 0.9%. The results from using "adjusted Stock Level" assuming the entire shortfall of 337 from Dr. Farber's unadjusted promotions model suggests that the pay difference is 1.3%, which continues to be well below Dr. Farber's 2.8% measure. Note that my adjustment to Dr. Farber's model for purposes of this adjustment to stock level is only to restrict the shortfall number to the class period. As noted above, I made several other changes to Dr. Farber's promotions model, one of which was to include time in level as a control when analyzing movements from level to level. As noted above, this change reduced the promotions shortfall from 337 to 215.[137] I turn next to using this number of shortfall reallocations of stock levels in the pay analysis.

<u>Pay differentials are even smaller when the corrections to Dr. Farber's promotion probit model are made in the simulation model</u>

174. As discussed above, I find that Dr. Farber omitted some important variables from his probit model of Stock Level advancement. In particular, he does not incorporate information on time in Standard Title and time in Stock Level, instead using age and time at Microsoft to control for tenure.

175. To bring my corrected shortfalls into the pay simulation-adjusted models, I also ran a version of the level adjustment analysis which builds on the results obtained when time in Standard Title and time in Stock Level are added to Dr. Farber's Stock Level advancement model. As shown above, when these variables are added, the resulting shortfall in female advancements is estimated to be 215. I therefore re-allocated 215 promotions from men to women, using the same methodology I used to re-allocate the 337 promotions from Dr. Farber's

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[137] The prior analysis had a shortfall of 207. However, in this analysis, I include no level to level promotion surpluses of women and thus 215 promotions are reallocated.

original model. After the Stock Levels were "reallocated," I again ran the pay regression, controlling for adjusted Stock Level. The resulting difference using the "adjusted" Stock Levels (based on reallocating 215 promotions from men to women) is -1.1%. Finally, after various further adjustments to Dr. Farber's approach discussed above, including taking into account supervisor effects, I found a total shortfall of 89 female promotions. Performing the Stock Level reallocation analysis once again, and re-running the aggregated pay analyses, I find that the aggregated percent pay difference between men and women is reduced to -0.9%. And when other variables that could impact pay differences between men and women are factored in (discussed in detail below), such as leaves of absence, hire source (college or lateral), part time status, promotion change indicator, and months in Stock Level, the pay difference falls to a very low level: -0.4%. A table summarizing the progression of the pay results models is below.

When Dr. Farber's Compensation Model 5 is Run Adding Stock Level With or Without First Adjusting Female Stock Levels Using Shortfalls of Female Promotions, the Gender Pay Difference Falls Dramatically

Model	Female Coefficient	T-Statistic	P-Value	Percent Diff.	Adj. R^2	Empl. Years
[1]	[2]	[3]	[4]	[5]	[6]	[7]
Dr. Farber's Model 5	-0.0287	-19.69	< 0.05	-2.8%	0.770	[redacted]
Dr. Farber's Model 5, **Control for Stock Level**	-0.0083	-9.75	< 0.05	-0.8%	0.909	[redacted]
Using Adjusted Shortfalls, and Adding Other Controls						[redacted]
Dr. Farber's Model 5, Control for Stock Level **reallocating 337** Shortfall	-0.0128	-14.66	< 0.05	-1.3%	0.908	[redacted]
Dr. Farber's Model 5, Control for Stock Level **reallocating 215** Shortfall	-0.0113	-12.99	< 0.05	-1.1%	0.909	[redacted]
Dr. Farber's Model 5, Control for Stock Level **reallocating 89** Shortfall	-0.0094	-11.04	< 0.05	-0.9%	0.909	[redacted]
Dr. Farber's Model 5, Control for Stock Level, 89 Shortfall, **add Other Controls**	-0.0042	-5.48	< 0.05	-0.4%	0.919	[redacted]

176. To conclude the analysis of pay at the aggregated level, when employees are compared according to their type of work, their levels of skills and responsibilities, as well as where they work, their professions, performance rating and other relevant variables, the difference in pay between men and women is 0.4%. This result continues to be statistically significant, largely because there are [redacted] observations in the analysis. In my opinion such a small pay difference is not practically significant, and there remains the possibility that omitted variables, such as prior experience, would explain this small difference.

177. It is now possible to reconcile the various findings of the performance rating, promotion and pay analyses. Performance is an important factor in setting pay and awarding promotions, as all of the information I have reviewed indicates. Both Dr. Farber and I agree that there are no performance rating differences between men and women at Microsoft within the putative class scope and time period. The fact that Dr. Farber's pay and promotion analyses are inconsistent with his finding on performance is because his pay and promotions analyses are flawed. When these analyses are re-done, there is virtually no promotions shortfall, and there is virtually no pay difference. Such outcomes reconcile with a performance process that is observed to be gender neutral.

178. The next sections of this report discuss other flaws in Dr. Farber's pay analysis that have been alluded to above.

Dr. Farber's pay analyses do not take amount of work and prior experience into account

179. There are a number of other factors relevant to pay that Dr. Farber does not take into consideration at all. For example, his data includes some part time employees. While it is not a common phenomenon, it occurs more among women than men and thus can impact the

measured gender pay difference. Dr. Farber also does not take leaves of absence into account. For example, Employee 161904 in Dr. Farber's data is a Senior Software Development Engineer whose base salary at level 64 was [redacted] despite holding the same Standard Title and Stock Level. The MS People data shows that she was on a leave of absence for 194 days and returned to work on a part time basis.[138] Neither her reduced days at work nor her part time status are accounted for in his compensation models.

180. Finally, I have noted the ways in which Dr. Farber's model does not compare apples to apples, based on the data we have for analysis. In many cases, employees who his model predicts should be paid the same, male and female alike, in reality have very different compensation. One possible reason for this is the lack of information on prior work experience and how current employees otherwise spent their time prior to coming to Microsoft. Recent research also suggests that in high wage, high skill occupations where the gender pay difference is declining more slowly than in other areas of the labor market, that one explanation may be that these are jobs in which flexibility – whether part year or part time work - is a distinct drawback. These tend to be jobs in which the work cannot be easily transferred from one worker to the next, where work is performed in teams that must stay in communication, and those jobs in which there are time pressures in the form of inflexible deadlines.[139]

[138] She was on LOA 10/12/2012-4/24/2013 (194 days). She came back part time on 4/25/2013, so on the 9/1/2013 date Dr. Farber uses to build his data, she was part time.

[139] Killingsworth, Mark R., and James J. Heckman. "Female labor supply: A survey." *Handbook of Labor Economics* 1 (1986): 103-204. Bertrand, Marianne, Claudia Goldin, and Lawrence F. Katz. "Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors." *American Economic Journal. Applied Economics* 2, no. 3 (2010): 228. Goldin, Claudia. "A grand gender convergence: Its last chapter." *The American Economic Review* 104, no. 4 (2014): 1091-1119. Blau, Francine D., and Lawrence M. Kahn. "The gender wage gap: Extent, trends, and explanations." *Journal of Economic Literature* 55, no. 3 (2017): 789-865.

Dr. Farber does not distinguish between new and lateral hires

181. When Dr. Farber studied gender pay differentials in the Goldman Sachs case, he took prior experience in the industry and whether someone was a lateral hire into account in his models.[140] He did so because he believed that these were important considerations in determining pay differences by gender in a non-discriminatory way. However, in the present matter, Dr. Farber does not control for lateral hires or for prior experience. That he does not have complete data on these factors for Microsoft employees does not make them irrelevant. It simply means that his estimated gender pay differences are simply measures of unknown differences, not discrimination.

182. For example, there are likely to be fewer unknown differences in productive characteristics between new college graduates than there are between those hired laterally: the quality of the school, their major, and perhaps summer internships may differ, but there are not likely to be large and substantial *unmeasured* differences between women and men. In contrast, consider those hired laterally into Microsoft. There is much we do not know about these employees. The only control Dr. Farber has for prior experience is age minus time at Microsoft. In other words, we do not know if the person was recruited from Apple, or lists his or her previous employer as the US Army. We do not know if that person took time off in between changing employers. There is likely to be a gender component to that decision, as women are more likely to take time off from work than are men.[141]

183. Patents held are a signal of innovation, for example, and it would be no surprise if Microsoft decided to pay those with patents more. There is research evidence to suggest patent

[140] "Specifically, I include controls for **work experience in related areas prior to Goldman, direct hires into Associate and Vice President positions (also called lateral hires**), division, year, office, education, AA job group, experience at Goldman, and experience at Goldman squared (both from the most recent hire date)." Expert report of Henry S. Farber in connection with *Chen-Oster v. Goldman Sachs*, February 17, 2014, page 19, emphasis added.

[141] Goldin, Claudia. "A grand gender convergence: Its last chapter." *The American Economic Review* 104, no. 4 (2014): 1091-1119. Blau, Francine D., and Lawrence M. Kahn. "The gender wage gap: Extent, trends, and explanations." *Journal of Economic Literature* 55, no. 3 (2017): 789-865.

rates differ by gender, even holding field of study constant.[142] Patents are a dimension of prior experience that is omitted from Dr. Farber's model.

184. There are clearly many dimensions of skills and prior experiences that laterally hired employees bring with them to Microsoft which are not systematically recorded in the MS People data, or within any of the other data systems maintained by Microsoft and that I am aware of. But the managers that work with and review these employees are aware of the existence of these skills and experiences, and that information is available to them to aid in decision making. These characteristics are simply not observable by the analyst, and therefore cannot be incorporated into the statistical models.

185. We can examine the potential effect of missing information by separating the new hires into two groups, one consisting of directly hired college graduates and the other comprised of lateral hires. The idea is that among college graduates, not having information regarding their pre-Microsoft background is unlikely to be an issue, since they came directly from higher education. Among laterals, there is clearly missing information that could explain how their initial pay was set and what skills and experiences they brought to their job at Microsoft. Thus, if the hypothesis is that it is missing information that is correlated with gender that is responsible for the small pay difference that remains after taking into account all of the data that *is* available, it is less likely there will be a gender difference in pay among the college group, for whom we have more job-related information than for the lateral hires, for whom proportionately more information is missing. The regression results for Engineers presented below support that hypothesis.

186. Separate regression models are estimated for the Engineering profession employees by hire source and candidate source. Hire source is a field from the job history data that is derived from the job requisition form – i.e., was the job expected to be filled by a lateral hire or a college

[142] Hunt, Jennifer, Jean-Philippe Garant, Hannah Herman, and David J. Munroe. *Why don't women patent?* No. w17888. National Bureau of Economic Research, 2012.

graduate.[143] There is another variable called "Candidate Source" that indicates a college hire or internet or other sources. I use these to indicate hire source. If an employee with hire source coded "Industry" or "N/A" was coded as "College" by the candidate source variable, I included them as a college hire. Rehires returning to Microsoft are excluded from the analysis. I then estimated Dr. Farber's model 5 (controlling for Standard Title but not Stock Level or other additional variables). The table below shows that there is no gender pay difference among the college hires. Among laterals, though, the gap is -2.9% adverse to women. The next row of the table controls for initial Stock Level, with the idea that the initial placement is a measure of the employee's prior experience and skills. When that variable is included in the regression, the gender gap in pay falls to just -0.6%. This is consistent with the hypothesis that prior experience is an unmeasured factor that differs by gender, and one that Dr. Farber did not account for in his pay models.

When Dr. Farber's Pay Model 5 is Run With or Without Adding Initial Stock Level and By Hire Source, the Gender Pay Difference Falls Dramatically

- Employees in Engineering Profession Hired After September 1, 2012 -

Total Compensation Using Farber's Model 5

Hire Source	Female Coefficient	T-Statistic	P-Value	Percent Difference	Adjusted R^2	Employee Years
[1]	[2]	[3]	[4]	[5]	[6]	[7]
College	0.001	0.27	0.79	0.1%	0.389	[redacted]
Lateral	-0.029	-6.11	< 0.05	-2.9%	0.610	
Lateral, With Control for Initial Stock Level	-0.006	-1.65	0.10	-0.6%	0.768	

Note: The number of employee-years analyzed is smaller because only new hires during the class period are included.

[143] August 25 Letter from Orrick to Plaintiffs re Structured Data Questions.

187. It is also the case that we have little information on what types of business products and specific areas within those products employees work on while at Microsoft. A worker in a highly productive or highly profitable unit could reasonably be expected to be paid more than someone with otherwise identical measured characteristics whose unit was less profitable. Similarly, a worker whose particular skills make her desirable to other employers might also be paid more than someone whose skills do not generate the same level of external interest from competitors, as her firm raises her pay to encourage retention. Microsoft documents mention Engineers particularly in this last regard, with the lowest tenure Engineers considered the highest retention risks.[144]

188. Consider [redacted] and [redacted] who in 2015 were employed as engineers at Microsoft under the same Standard Title of "Senior Software Development Engineer." These two employees were assigned the same salary grade level of 63 and both would receive a promotion during 2015. At this time [redacted] and [redacted] also had comparable levels of experience as both employees were in their mid-thirties ([redacted]) and had been employed at Microsoft for [redacted]. However, as can be seen from their promotion justification comments, [redacted] and [redacted] day to day responsibilities appear to have been substantially different. Whereas [redacted] worked on specific and technical tasks related to "monitoring and reporting infrastructure," [redacted] tasks seem broader and generally involved him taking a leadership role, such as when he was "independently leading v-teams of developers on AP architectural changes for the past 24 months" and maintained "familiarity with industry trends" in addition to his technical knowledge. This may be related to the Microsoft Function they worked in: [redacted] worked in "Azure Compute" while [redacted] worked in "Azure Storage."

[144] "Promotion rates are faster for early in career employees, particularly in E&R where market pressures are the strongest." MSFT_MOUSSOURIS_00004282

[redacted] **Personnel Number: 372833** [redacted]	[redacted] **Personnel Number: 203339** [redacted]
[redacted]	[redacted]

189. Differences in work duties persist even when considering only the individual and technical work of these engineers. [redacted] appears to have been primarily focused on designing and developing features for Excel, as he was responsible for a [redacted] and the [redacted] This is in comparison to [redacted] whose work seems to have been focused on Microsoft's more advanced and "cutting edge" products, such as his design of [redacted] [redacted] It appears from these descriptions that despite their shared Standard Title of

"Senior Software Development Engineer" and shared Stock Level, [redacted] and [redacted] had very different responsibilities.

190. As another example, [redacted] and [redacted] both [redacted] with [redacted] of experience at Microsoft, were employed at salary grade level 62 with the Standard Title of "Software Development Engineer 2" in 2015. Despite these similarities, comments by [redacted] and [redacted] managers highlight the differences in the work they performed.

[redacted] **Personnel Number: 357178** [redacted]	[redacted] **Personnel Number: 287612** [redacted]
[redacted]	[redacted]

191. They worked in different functional areas, [redacted] in Personal Devices & Sensors and [redacted] in Azure Storage. Whereas [redacted] delivered on complex projects and [redacted] worked in more of a managerial capacity. His leadership skills were frequently praised as he [redacted] and was [redacted] was also specifically said to be effective at [redacted] promotion amount was much higher than [redacted] For [redacted] there is no mention of any task requiring leadership or even group collaboration. Clearly for such a large organization, more than an employee's position title must be taken into consideration to properly account for a particular employee's duties at work.

192. Perhaps [redacted] had relevant prior work experience. Despite being the [redacted] he has [redacted] at Microsoft. Education and prior work experience are employee characteristics that labor economists agree are relevant when studying earnings.[145] The human capital literature also suggests that in circumstances where other factors also bear a relationship to productivity, those factors ought to be incorporated into pay and promotion models as well.[146]

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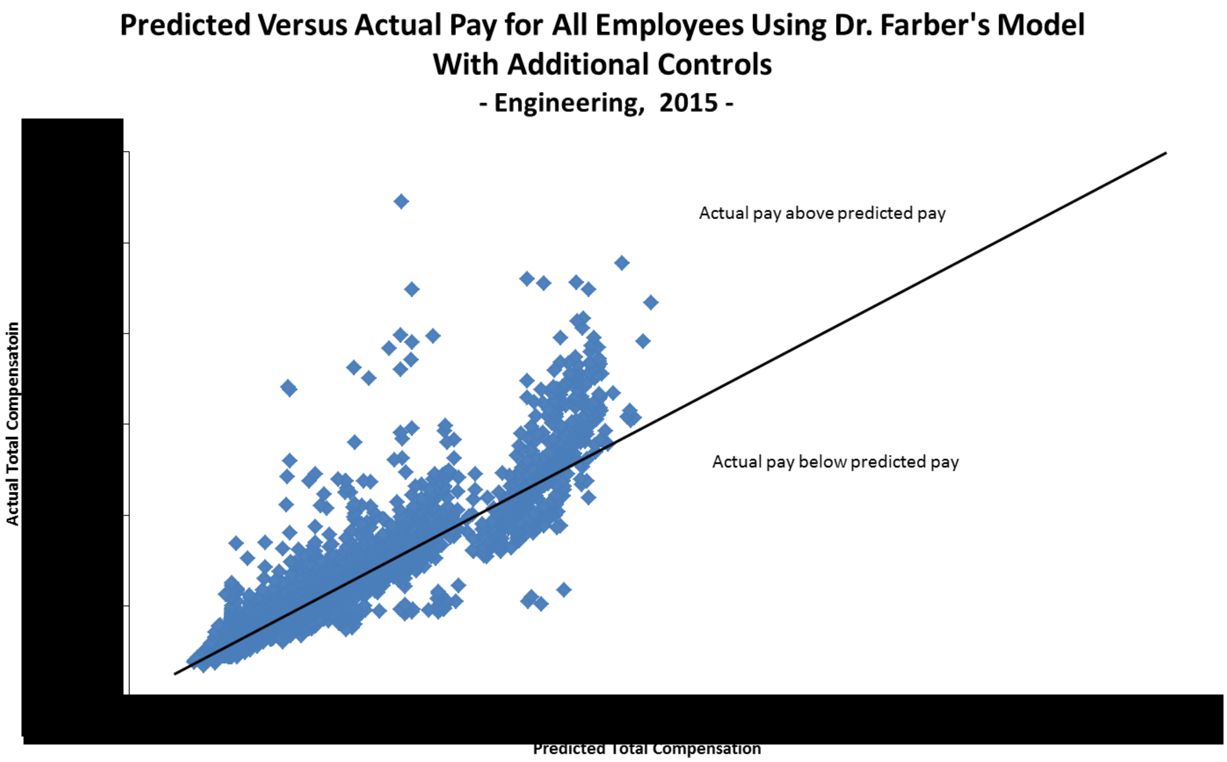
[145] A selection of these references includes Becker, Gary S. "Human Capital," 1964, 2nd Edition, New York, NY: National Bureau of Economic Research; Mincer, Jacob (1958). Investment in Human Capital and Personal Income Distribution. *Journal of Political Economy* 66 (4): pp. 281-302; Mincer, Jacob (1974). *Schooling, Experience and Earnings.* New York, National Bureau of Economic Research; distributed by Columbia University Press; Mincer, Jacob, "On-the-Job Training: Costs, Returns, and Some Implications," *Journal of Political Economy*, Supplement to Vol. 70, 1962; Willis, Robert J. "Wage Determinants: A Survey and Reinterpretation of Human Capital Earnings Functions." *Handbook of Labor Economics* 1 (1986): 525-602.

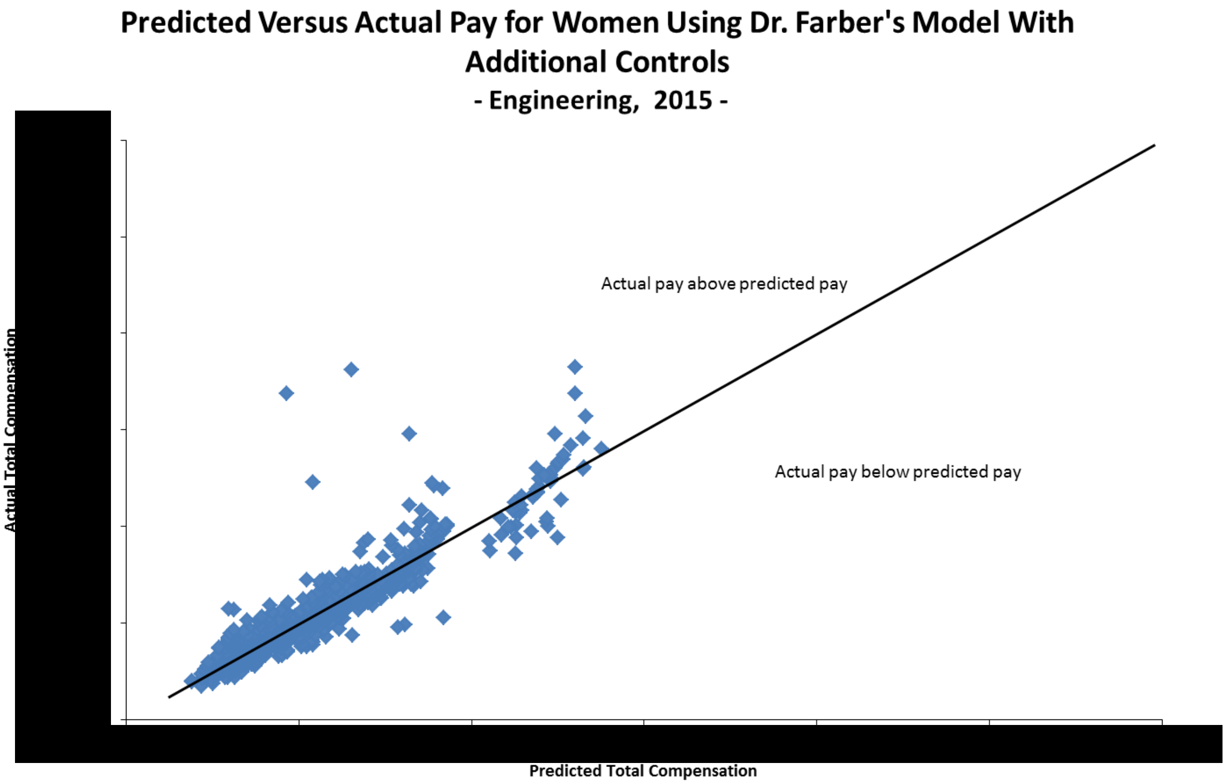
[146] Haltiwanger, J., J. Lane and J. Spletzer (June 2007) "Wages, Productivity, And The Dynamic Interaction Of Businesses And Workers," *Labour Economics*, 14(3), pp. 575-602; Abowd, J., F. Kramarz and D. Margolis (1999) "High Wage Workers And High Wage Firms," *Econometrica*, pp. 251–334; Goldin, C. and L.F. Katz, "Technology, Skill, And The Wage Structure: Insights From The Past," *American Economic Review, May* 86 (1996) (2), pp. 252–257.

193. It is instructive to plot predicted versus actual pay using my adjustments to Dr. Farber's pay model. The overall aggregated impact of gender on pay is *de minimis* - 0.4%. The graph below for Engineers only in 2015 is derived from the above model controlling for Dr. Farber's Model 5 variables plus Stock Level, promotion indicator, part time work, leaves of absence and hire source, but does not control for gender. The graph plots actual pay for each employee on the vertical axis and what their expected pay would be based on factors other than gender on the horizontal axis. The solid black line indicates where actual pay equals predicted pay. Dots above the black line indicate employees who are paid above what the model predicts; dots below the line indicate employees who are paid less than the model predicts. For example, take the point along the horizontal axis at [redacted], which is where predicted pay equals [redacted] If one were to draw a straight line vertically from that point toward the title of the graph, and which intersected with a dot for an employee below the black line, that would indicate someone who was paid below the predicted level of [redacted]. If one were to continue that same line up from [redacted] and intersect it with an employee dot above the black line, that is someone whose actual pay is higher than the predicted [redacted]. Both dots represent employees who, based on their observable characteristics were predicted to be paid [redacted], but one person is paid more than the expected [redacted] and the other person is paid less. This difference in actual pay between two observationally similar employees is unexplained by the regression model, because the model makes the same average prediction for both employees.



Note: Chart excludes outliers earning over $1.5M. Dr. Farber's Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Additional controls include Stock Level, months in Stock Level, promotion indicator, part time indicator, leaves of absence, and hire source. Gender control is excluded when calculating predicted pay.

194. Now consider Plaintiffs' hypothesis that women are discriminated against in pay. If that is the case, then one would expect to find women largely below the black line in the above graph, because their actual pay would typically be below their predicted pay. The graph below is the same as the one above, except it is restricted just to women. It is immediately obvious that women are evenly distributed above and below that black line where actual pay equals predicted pay. That is what a gap of -0.4% means – that women are generally distributed above and below their predicted value and that the difference is close to 0. Even accounting for the "adjusted" Stock Level issue discussed above, the estimated gender pay difference is 0.4%, which would not make even a perceptible difference in these charts.

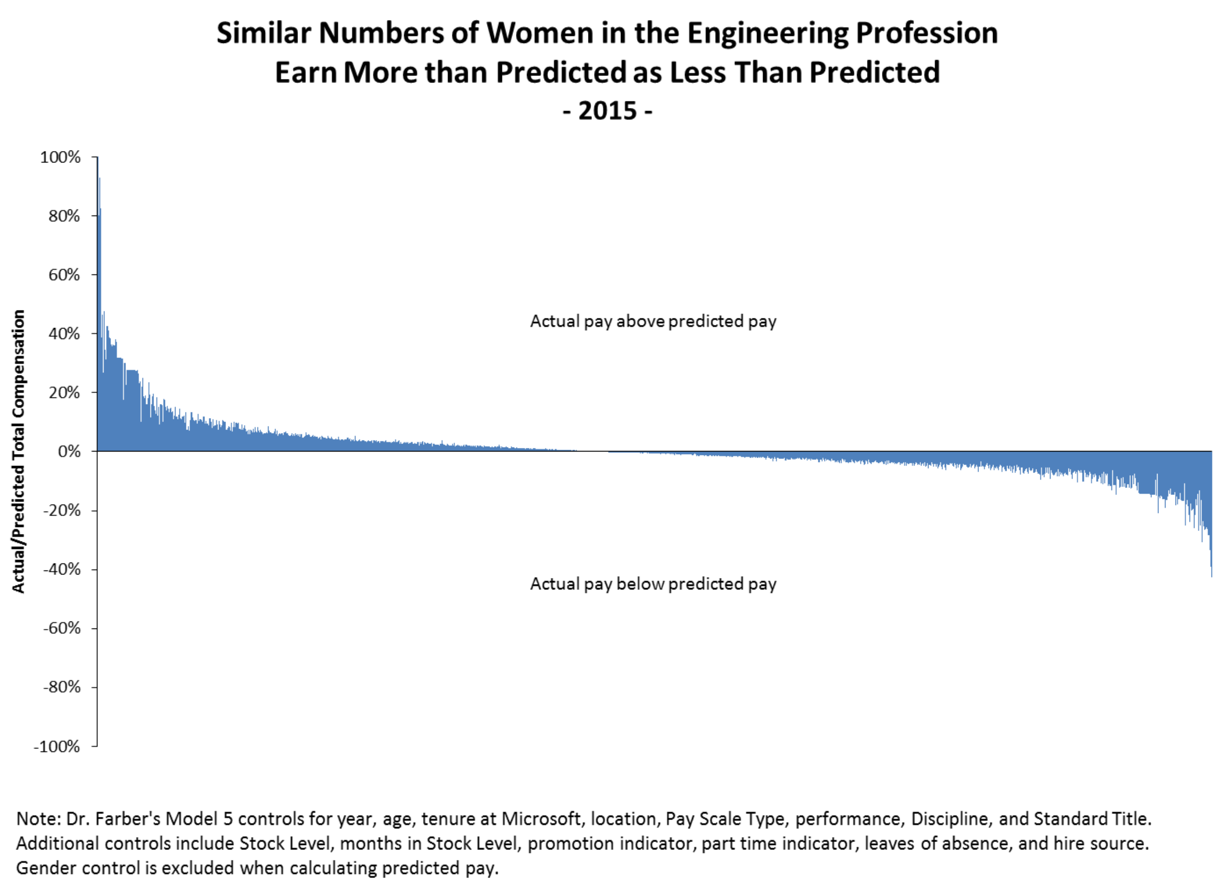


Note: Dr. Farber's Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Additional controls include Stock Level, months in Stock Level, promotion indicator, part time indicator, leaves of absence, and hire source. Gender control is excluded when calculating predicted pay.

195. The graph below displays the same information as that above, but portrays it somewhat differently. As before, an employee whose actual pay is greater than her predicted pay is plotted above the horizontal axis and an employee whose actual pay is less than her predicted pay is plotted below the axis. The height of the bar measures each female employee's actual pay divided by her predicted pay, multiplied by 100.[147] Thus, this ratio can be interpreted as the percentage by which actual pay differs from predicted pay. Employee outcomes are sorted from highest to lowest. If most or all women were adversely affected by Microsoft's pay policies and practices, they would largely or entirely appear below the horizontal zero axis – i.e., their

[147] These are also re-normalized to zero for ease of visual interpretation, such that women who earn more than predicted are above the horizontal axis at zero and women who earn less than predicted are below the horizontal axis.

percentages would be negative when comparing actual to predicted or "should have been" pay. The graph shows instead that women are not systematically adversely situated relative to men: The bars are fairly evenly distributed both above and below the line at zero. That the height of the bars ranges from positive to negative shows that one size does not fit all, even with the additional variables I have used in the regression model, and that a single regression coefficient is a summary measure that masks a great deal of variation in *regression controlled* outcomes in the underlying data for women. I turn next to examining the representation of women at Microsoft to external labor benchmarks.



FEMALE REPRESENTATION COMPARED TO CENSUS BENCHMARKS

196. Plaintiffs' claimed in their SAC that Microsoft values less the contributions of women.[148] If this were the case, women might be less likely to want to work at Microsoft. It is possible to compare the representation of women at Microsoft to external benchmarks. A method that labor economists often use to study the representation of specific demographic groups at particular companies is comparison to external benchmarks, such as government data. Census data can be used to construct measures of female representation in the labor market. In this section, I compare the proportion of women in "technical and engineering roles" at Microsoft to the proportion of women in similar jobs in the labor market. I find that women's representation at Microsoft equals or exceeds the representation of women in similar positions in the external labor market benchmarks.

197. A widely accepted approach to studying the composition of individuals employed by a particular company relies on comparing representation at that company to the specific labor market within which the company operates. The logic is that if a company operates in the same labor market as its competitors, then looking at the composition of the overall labor market can provide a benchmark against which a specific company may be compared. In other words, if we analytically narrow to the jobs and industries in question and focus on the appropriate segment of qualified individuals, we will be able to get a sense for what any given company's representation in that intersection of attributes would look like, on average. We can then compare the company's actual representation to these benchmarks.

[148] Plaintiffs' Motion for Class Certification, p. 2, lines 10-11: "The Calibration Process operates within the context of a corporate culture that systematically devalues women's contributions"

198. To conduct the studies, I relied on publicly-available and widely-used US Census American Community Survey (ACS) data. The US Census Bureau releases large-scale individual-level data from the ACS every year. These data are referred to as “micro-data” in that they allow the analyst to view records for randomly chosen and thus representative anonymous individual ACS respondents, along with an extensive set of demographic, economic/occupational, and residential characteristics. As part of each individual’s record in the ACS files, an analyst can identify the gender of the respondent, annual earnings, labor force status, industry affiliation, specific job title, as well as numerous other personal and occupational characteristics. The data I relied on was collected annually from 2013 to 2016 and included respondents from across the United States.

199. The Census Bureau has developed industry and job classification codes, such that analysts using the data can focus on specific groups of workers and determine the characteristics about members of the specific group(s) in question. Statistics for any particular group can be computed using large geographic areas (e.g. nationally) or can be restricted to smaller geographic regions. For these analyses, the ACS data were limited to include those working in the “Software Developers” occupational code (code 1020), which represents the Census classification most closely aligned with the work performed by Software Engineers at Microsoft. Additionally, the ACS’s “class of worker” variable was used to restrict the data to respondents who reported working for private, for-profit companies or businesses for wages, salary or commission. The restriction was imposed to exclude respondents who reported being self-employed or working in the public sector. Only those who reported working more than 48 weeks during the year were selected, in order to exclude those who reported partial-year wages.

Lastly, any remaining respondents who reported no wages in a particular year were excluded from the ACS sample data.

200. In conducting an external benchmark analysis with highly compensated employees, it is important to ensure that the benchmarks are calculated with consideration to earnings. If the earnings at a particular company are higher when compared with the earnings of typical workers within a given job classification, it may be inappropriate to estimate a benchmark using workers at all levels of the income distribution. In calculating a representation benchmark, for example, less weight should be given to ACS respondents whose earnings are dissimilar from the company in question. Similarly, more weight should be given to ACS respondents whose annual earnings are similar to those employed by the company being studied. The reason that earnings are considered is that labor economists consider pay to be a proxy for level of skill and responsibility in a functioning labor market, and demographic characteristics may not be distributed independently of earnings/skill levels.

201. In order to calculate the appropriate earnings weights for the benchmark analysis, Microsoft data were used to calculate the total compensation for each Microsoft employee on a fiscal year basis (including annual salary, stock grants and performance-based bonuses).[149] Once each individual's total annual compensation was determined, the distribution of compensation amounts was split into deciles (e.g. 10th-20th percentile, 20th-30th percentile). Each decile grouping encompassed a specific salary range (e.g. those in the 40th-50th decile earned between [redacted] in 2014, etc.). Since decile groupings were used, each group included approximately 10% of the relevant Microsoft employee population, by definition.

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[149] For this analysis, the following Standard Titles were selected: Software Engineer, Software Development Engineer, Software Development Engineer 2, Senior Software Development Engineer, Software Development Engineer in Test, and Software Developer Engineer in Test 2. Taken together, the employees in this grouping of job titles account for approximately 46% of the relevant work force within Microsoft.

202. Next, each ACS respondent was assigned to one of the 10 Microsoft-derived compensation income decile ranges based on their reported annual earnings (including bonuses).[150] The Microsoft representation in each income decile range (approximately 10%) was then compared to the representation in each income decile range within the Census ACS data. Each respondent in the ACS data was assigned a weight based on their income bracket's representation in the ACS, relative to that bracket's representation at Microsoft. For example, individuals earning between [redacted] represent 10% of employees at Microsoft. Individuals earning within this range represent 66.9% of those surveyed for the Census ACS. The ratio between these two numbers is (10/66.9), or .149. Thus, this number or "weight," was assigned to each of the ACS respondents in this particular income range. Again, the goal was to assign appropriate weight to ACS respondents based on how closely their annual earnings reflect the earnings of those working at Microsoft.

The representation of women at Microsoft is well above Census benchmarks

203. The income-weighted female representation within the ACS Software Developers occupational code was calculated by applying the weights established from the Microsoft compensation distribution.[151] Female representation was determined across the entire 2013-2016 period as well as on a per-year basis. These results are shown in the table below. The first line on the exhibit shows that ACS female representation among Software Developers from 2013 to 2016 was 12.06%. During this same period of time, female representation at Microsoft was 14.06% among Software Engineers and those with similar Standard Job Titles. Thus, the female

[150] The ACS variable WAGP was used, adjusted for yearly fluctuations using the ADJINC variable.
[151] These calculations used the income distribution weighting as well as the ACS person-weight variable PWGTP.

representation at Microsoft exceeded the benchmark for Software Developers established by the ACS.

Comparison of Female Representation
at Microsoft and in the 2013-2016 Census ACS
ACS Weighting is Based on the Compensation Distribution at Microsoft During the Year
Microsoft Job Titles: Software Engineers/Software Development Engineers
ACS Occupation Classification: Software Developers
- No Industry Restriction -

	Microsoft			Census ACS	
Salary Year	**Number of Employees**	**Number of Female Employees**	**Microsoft Female Representation**	**Number of ACS Observations**	**Income-Weighted ACS Female Representation**
[1]	[2]	[3]	[4]	[5]	[6]
2013-2016	63,377	8,908	14.06%	35,752	12.06%
2013	15,357	2,176	14.17%	8,178	13.91%
2014	15,370	2,199	14.31%	8,528	12.26%
2015	14,999	2,140	14.27%	9,060	12.29%
2016	17,651	2,393	13.56%	9,986	10.16%

Note: Microsoft Standard Job Titles included are: Software Engineer, Software Development Engineer, Software Development Engineer 2, Senior Software Development Engineer, Software Development Engineer in Test, and Software Development Engineer in Test 2. Census Occupation Code: 1020 (Software Developers). Both tabulations of ACS female representation use the Census person-level weight "PWGTP".

204. Within the Software Developers occupational code, there were ACS respondents who reported working in industries that are not comparable with Microsoft's industry. These industries include Banking, Finance, Insurance, Aeronautics, etc. The most appropriate Census industry code within the Software Developer occupational code is "Computer Systems Design and Related Services". This is the industry code identified by more than 40% of ACS Software

Developers and is the most common industry reported among those with this occupational classification. After restricting the benchmark analysis to those working exclusively in this particular industry, the ACS female representation among Software Developers was 10.96% during 2013-2016. Thus, with an industry-restriction imposed, female representation at Microsoft continues to exceed the benchmark obtained from the ACS.

205. Additionally, the ACS benchmark analysis was conducted for California and Washington State specifically (where a combined total of 95% of Microsoft employees were located during the class period). This analysis yielded similar results to the ACS benchmark analyses previously presented. During the period from 2013 to 2016, ACS female representation is estimated to be 12.07% with no industry restriction and 11.27% with the industry restriction. In both cases, the Microsoft female representation among Software Engineers from 2013 to 2016 (14.06%) exceeded the ACS benchmark numbers.

CONCLUSION

206. Plaintiffs claim in their Second Amended Complaint that gender bias in the performance evaluation process leads to biased outcomes in both pay and promotions. There is no support for this hypothesis evident in the Microsoft data. Both my analysis as well as Dr. Farber's analysis demonstrates that there is no difference in performance ratings between men and women over the period 2012 through 2015 in the employee population at issue in this case. Furthermore, my analysis also shows that during the calibration process, whereby initial ratings are modified leading to a final rating, female ratings are either not modified differently than male ratings, or are modified very slightly upwards. Thus there is no empirical basis to claim that performance rating and performance rating "calibration" is causally related to differences in pay or promotion

outcomes among the putative class members. For example, while ratings are very important in explaining pay generally, both Dr. Farber and I show that including performance rating in the statistical analysis does not change the female coefficient in the pay statistical model.

207. Regarding pay, there is no aggregate substantive difference within the employee population at issue in this case. Dr. Farber's model fails to control for large and meaningful differences in skill and responsibility within the employee population, even though he testified that this is important to do. When pay is correctly analyzed, the bottom line aggregate pay difference is tiny, well under a half of one percent. And when promotions are examined correctly, there is very little aggregate difference in female promotions. Delving into the many sub-strata within this complex employee population shows that female employees in the IT Operations profession experience no shortfall in promotions, under either my or Dr. Farber's approach. Looking at both Engineering and IT Operations profession employees during the regular promotion cycle reveals no shortfall in promotions, again, under either my model or that of Dr. Farber. Looking at Engineering profession promotions taking place outside of the "annual review" period, there is a small shortfall which, based on inference from the constellation of other aggregate findings, is likely attributable to unmeasured and idiosyncratic factors. The representation of women at Microsoft among software engineers equals or exceeds external labor market benchmarks.

208. Taken together, it is difficult to argue from a labor economics perspective that the small remaining differences in promotions are statistical evidence of discrimination against women, since in every other area, and for the vast majority of promotion decisions as well, there is virtual parity between men and women. The more likely inference is that there are unknown factors

which are correlated to gender, which if were able to be taken into account, would likely eliminate the one remaining area of difference.

209. Putting aside the aggregate findings, there is enormous variety in both circumstances as well as outcomes for the employees and the putative class in this employee population. While the analysis of annual review promotions at the aggregate level shows virtually no difference between men and women, viewing the outcomes for women under different supervisors reveals considerable variety. This indicates either the likely presence of unknown idiosyncratic factors, or that different supervisors behaved in ways unknowable from the data. With such a widely varying employee population, whose pay ranges from [redacted], whose jobs range from art design to advanced computer science, whose education runs the gamut from high school to double Ph.D.'s, who work in a wide variety of departments on dozens of different products, it is not surprising that any statistical model one would apply would not fit all these circumstances.

Executed this 5th day of January, 2018 in Los Angeles, California.

Ali Saad, Ph.D.

APPENDIX 1

APPENDIX 1:

VARIABILITY ANALYSES BY YEAR

Actual and Predicted Pay According to Farber's Model 5

- Corresponds to Chart in Saad Report -

Named Plaintiff / Declarant	Year	Actual Total Compensation	Predicted Total Compensation	Standardized Residual
Muenchow	2011	[redacted]	[redacted]	-1.210
	2012	[redacted]	[redacted]	-1.334
	2013	[redacted]	[redacted]	-1.345
	2014	[redacted]	[redacted]	-1.365
	2015	[redacted]	[redacted]	-1.214
	2016	[redacted]	[redacted]	-1.854
Moussouris	2012	[redacted]	[redacted]	1.686
	2013	[redacted]	[redacted]	1.857
	2014	[redacted]	[redacted]	1.731
Alberts	2011	[redacted]	[redacted]	-0.125
	2012	[redacted]	[redacted]	0.038
	2013	[redacted]	[redacted]	0. 429
	2014	[redacted]	[redacted]	1.384
	2015	[redacted]	[redacted]	0.914
	2016	[redacted]	[redacted]	0.597
Boeh	2011	[redacted]	[redacted]	0.089
	2012	[redacted]	[redacted]	-0.082
	2013	[redacted]	[redacted]	0.336
	2014	[redacted]	[redacted]	0.416
Dove	2011	[redacted]	[redacted]	2.112
	2012	[redacted]	[redacted]	2.595
	2013	[redacted]	[redacted]	5.090
	2014	[redacted]	[redacted]	3.592
	2015	[redacted]	[redacted]	3.505
	2 016	[redacted]	[redacted]	3.197
Hutson	2013	[redacted]	[redacted]	0.646
	2014	[redacted]	[redacted]	0.699
	2015	[redacted]	[redacted]	0.504
Smith	2014	[redacted]	[redacted]	-1.239
	2015	[redacted]	[redacted]	-1.640
	2016	[redacted]	[redacted]	-0.483
Sowinska	2011	[redacted]	[redacted]	2.305
	2012	[redacted]	[redacted]	1.624
	2013	[redacted]	[redacted]	1.693
	2014	[redacted]	[redacted]	1.633
	2015	[redacted]	[redacted]	1.613
Underwood	201 5	[redacted]	[redacted]	0.470
	2016	[redacted]	[redacted]	0.814
Vaughn	2016	[redacted]	[redacted]	-0.509
Warren	2014	[redacted]	[redacted]	-1.557
	2015	[redacted]	[redacted]	-1.698
	2016	[redacted]	[redacted]	-1.138

Actual and Predicted Promotion Probability for Named Plaintiffs and Declarants Using Farber's Probit Model*

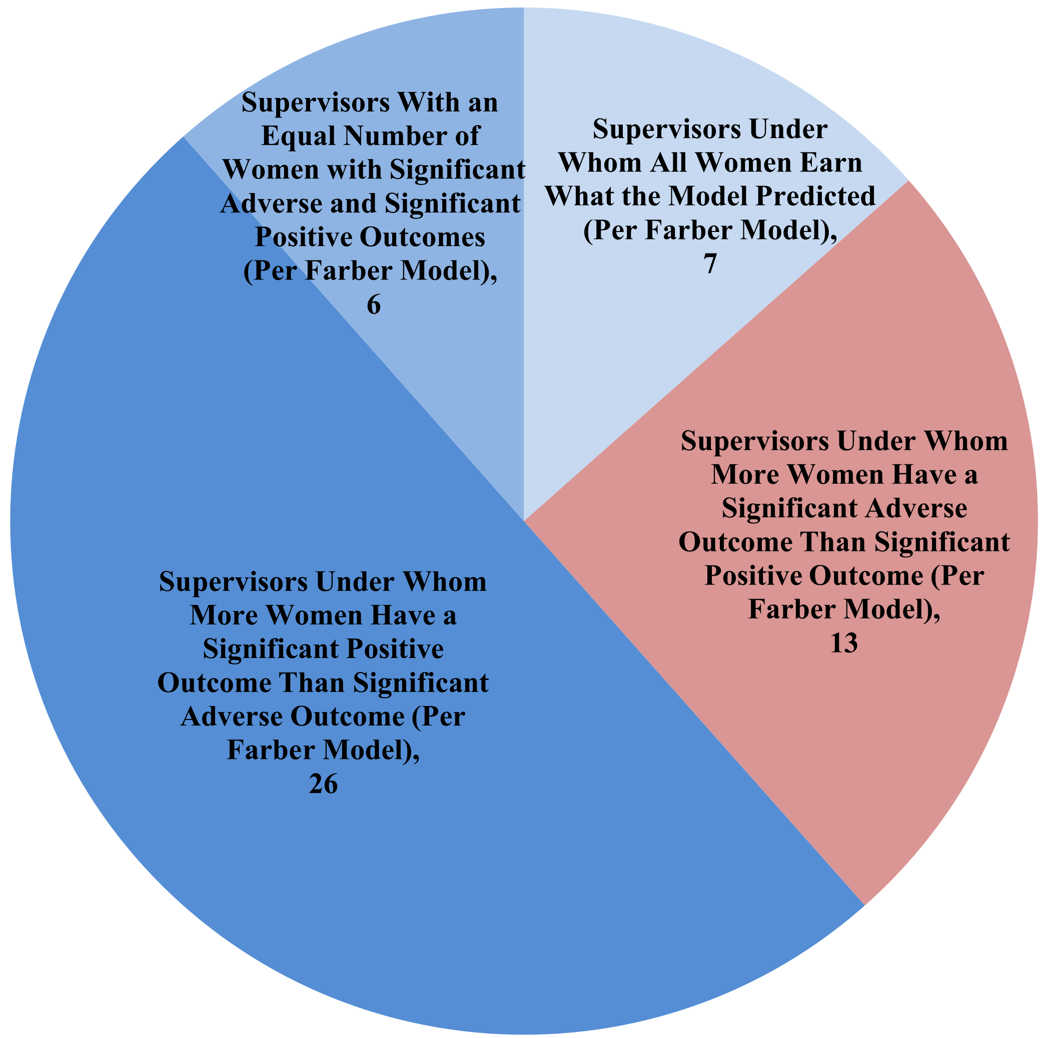
- Promotion Defined as Increase in Stock Level Compared to Following Year -

Named Plaintiff / Declarant	Year	Promotion?	Predicted Promotion Probability
Moussouris	2012	No	0.037
	2013	No	0.214
Muenchow	2011	No	0.044
	2012	Yes	0. 228
	2013	No	0.371
	2014	No	0.051
	2015	No	0.368
Alberts	2011	Yes	0.661
	2012	No	0.434
	2013	Yes	0.468
	2014	No	0.124
	2015	No	0.146
Boeh	2011	Yes	0.376
	2012	No	0.260
	2013	No	0 .077
Hutson	2013	No	0.002
	2014	No	0.000
Smith	2014	No	0.002
	2015	No	0.002
Underwood	2015	No	0.177
Warren	2014	No	0.611
	2015	Yes	0.696

Note: Gender was taken o ut of the model.

Level 2 Supervisors: Pay Outcomes for Women (Farber Model 5)

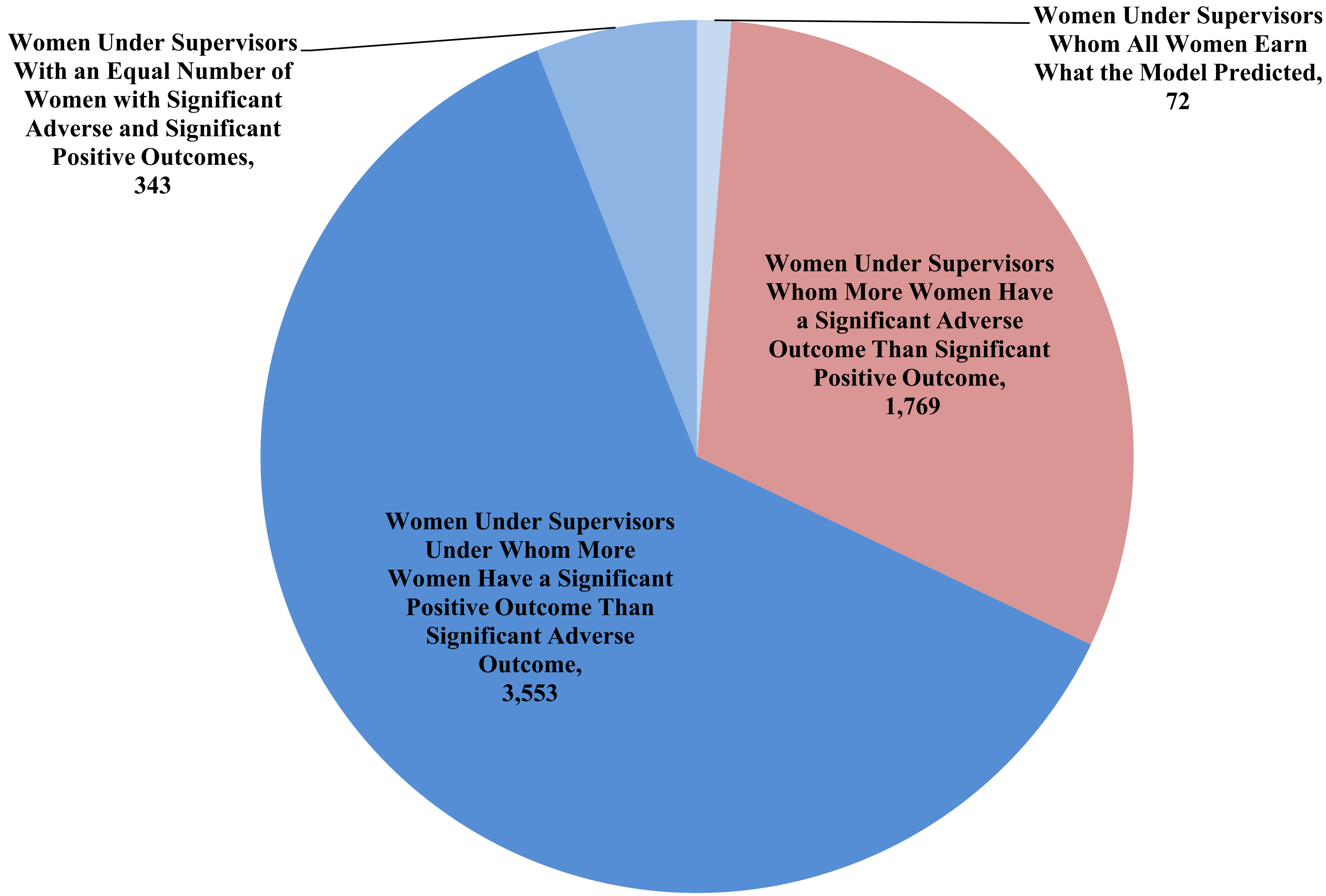
- Engineering & IT Operations, 2015 -



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 2 supervisors with at least 10 employees and accounts for 99% of female employees.

Pay Outcomes for Women By Level 2 Supervisor Category (Farber Model 5)

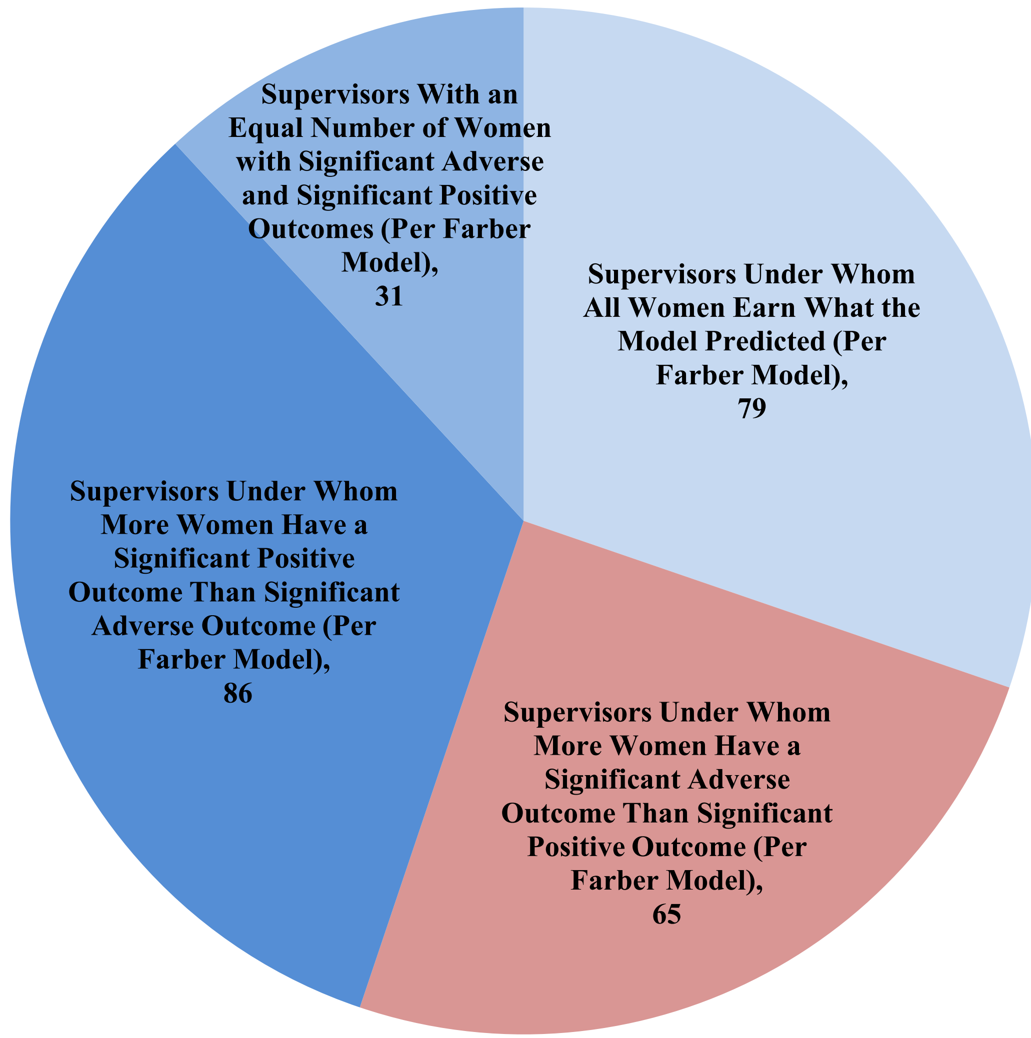
- Engineering & IT Operations, 2015 -



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 2 supervisors with at least 10 employees and accounts for 99% of female employees.

Level 3 Supervisors: Pay Outcomes for Women (Farber Model 5)

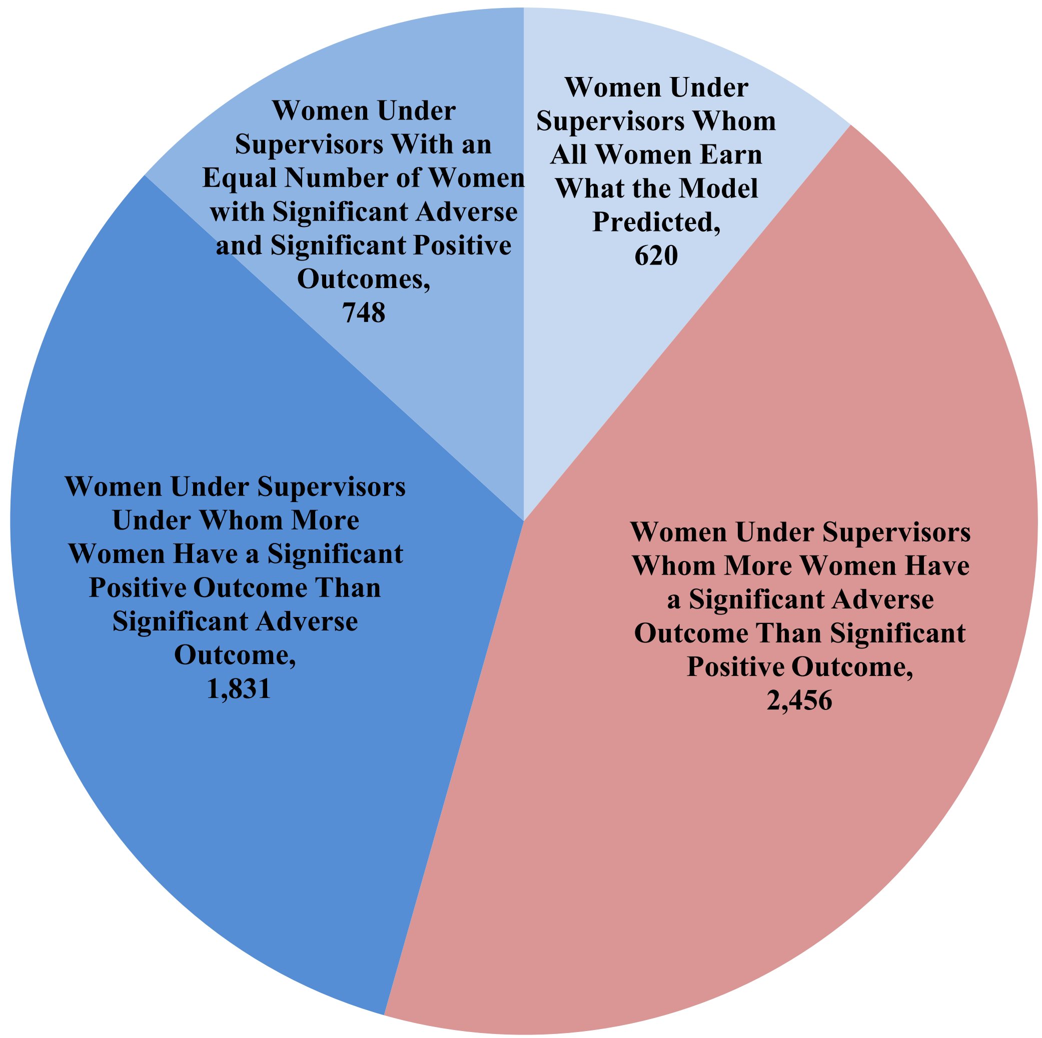
- Engineering & IT Operations, 2015 -



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 3 supervisors with at least 10 employees and accounts for 98% of female employees.

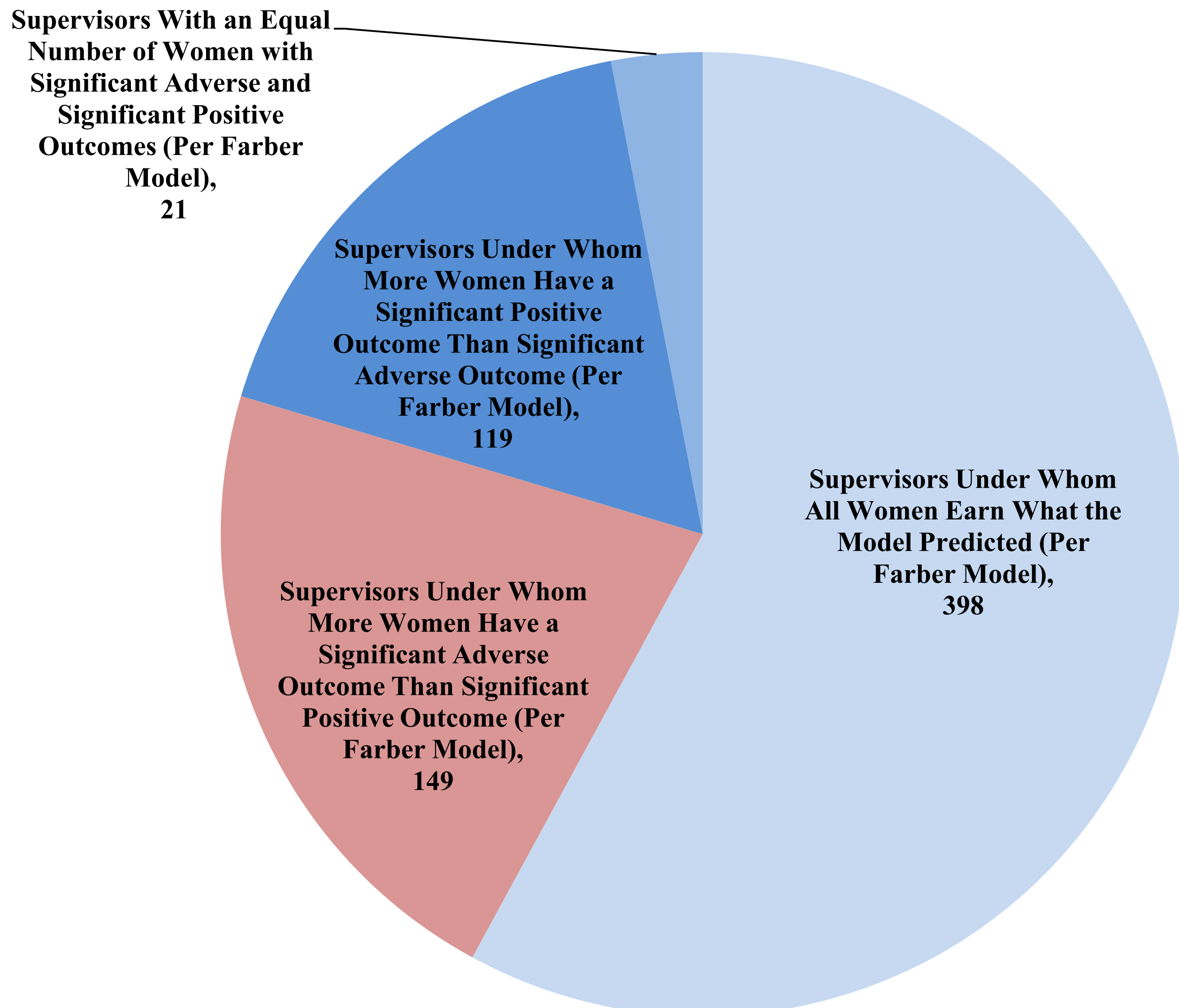
Pay Outcomes for Women By Level 3 Supervisor Category (Farber Model 5)

- Engineering & IT Operations, 2015 -



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 3 supervisors with at least 10 employees and accounts for 98% of female employees.

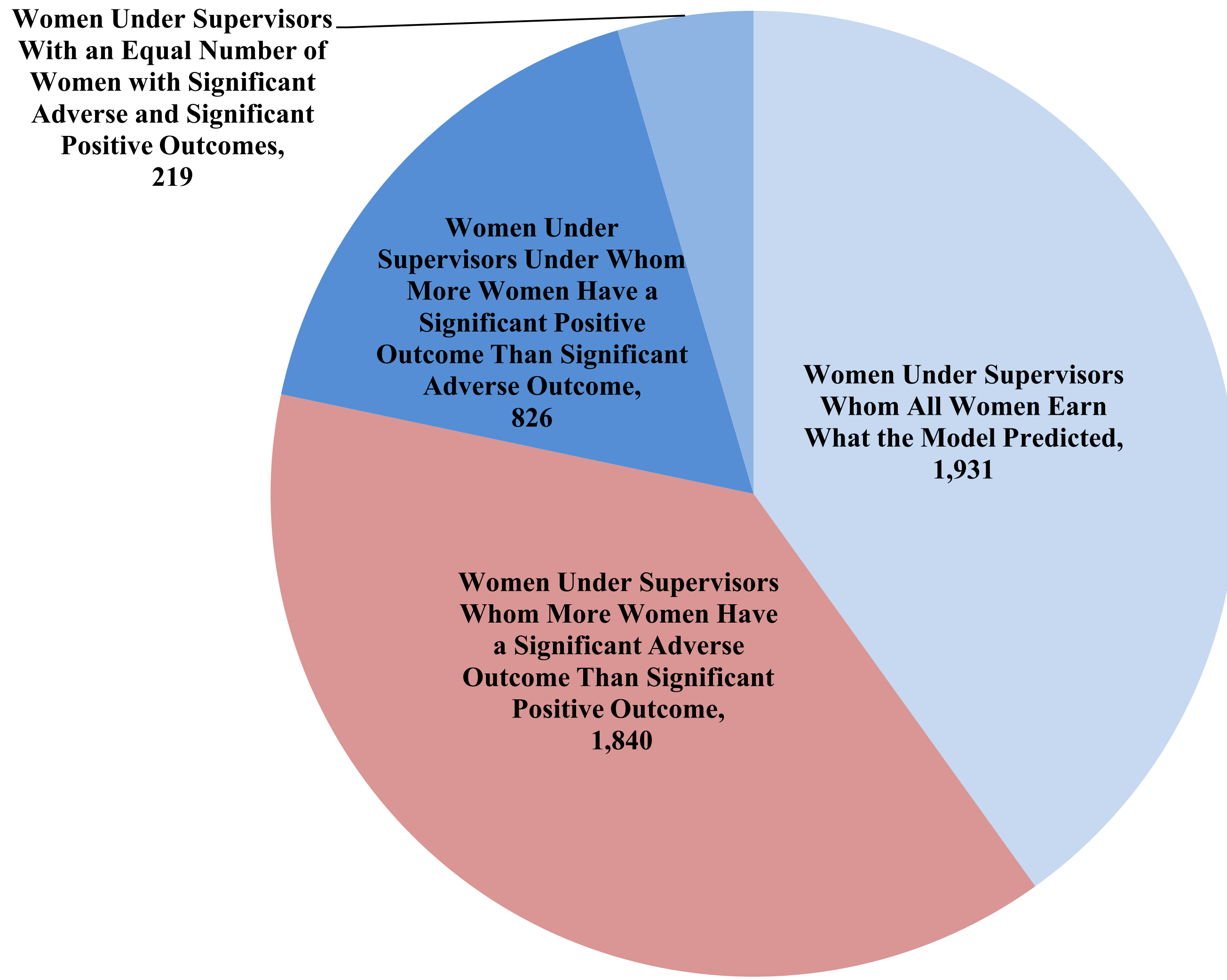
Level 4 Supervisors: Pay Outcomes for Women (Farber Model 5)
- Engineering & IT Operations, 2015 -



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 4 supervisors with at least 10 employees and accounts for 83% of female employees.

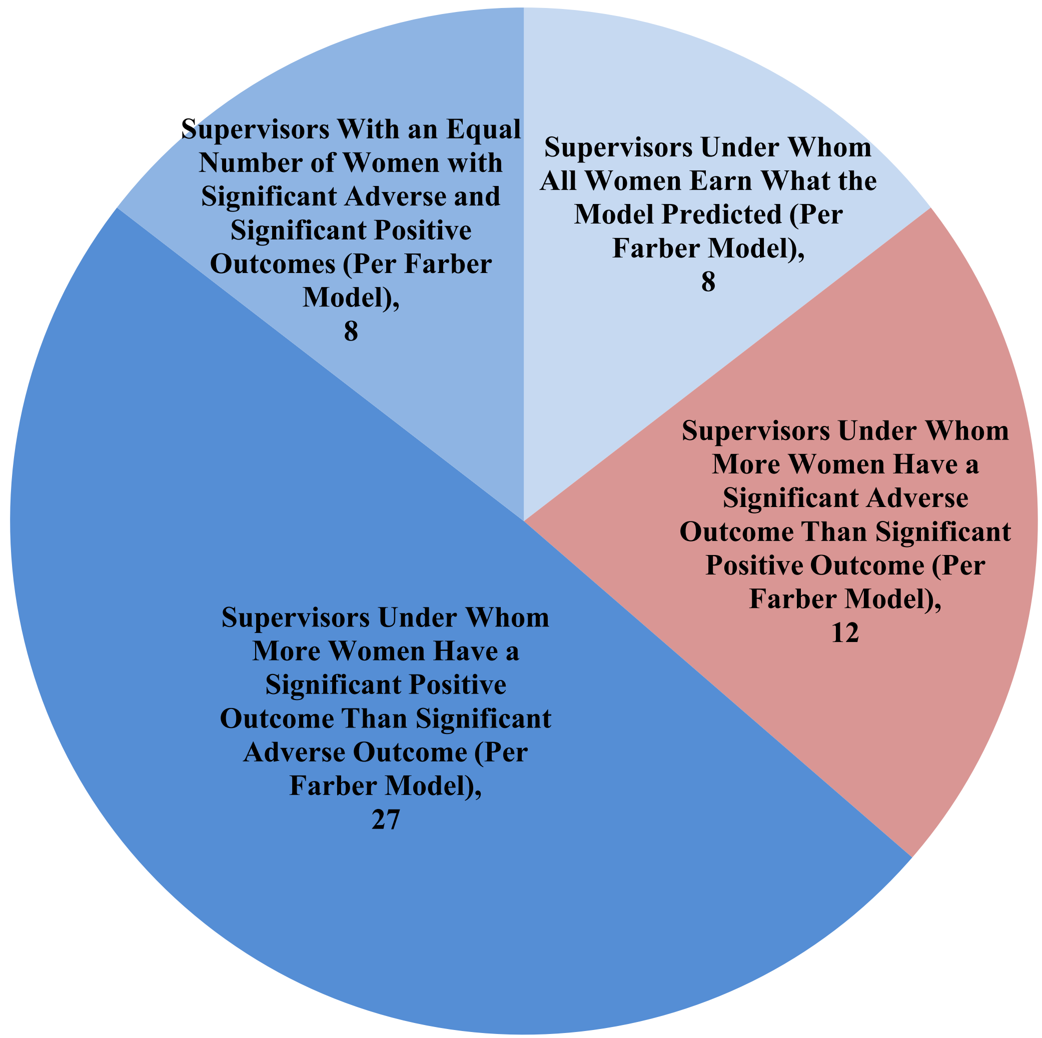
Pay Outcomes for Women By Level 4 Supervisor Category (Farber Model 5)

- Engineering & IT Operations, 2015 -



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 4 supervisors with at least 10 employees and accounts for 83% of female employees.

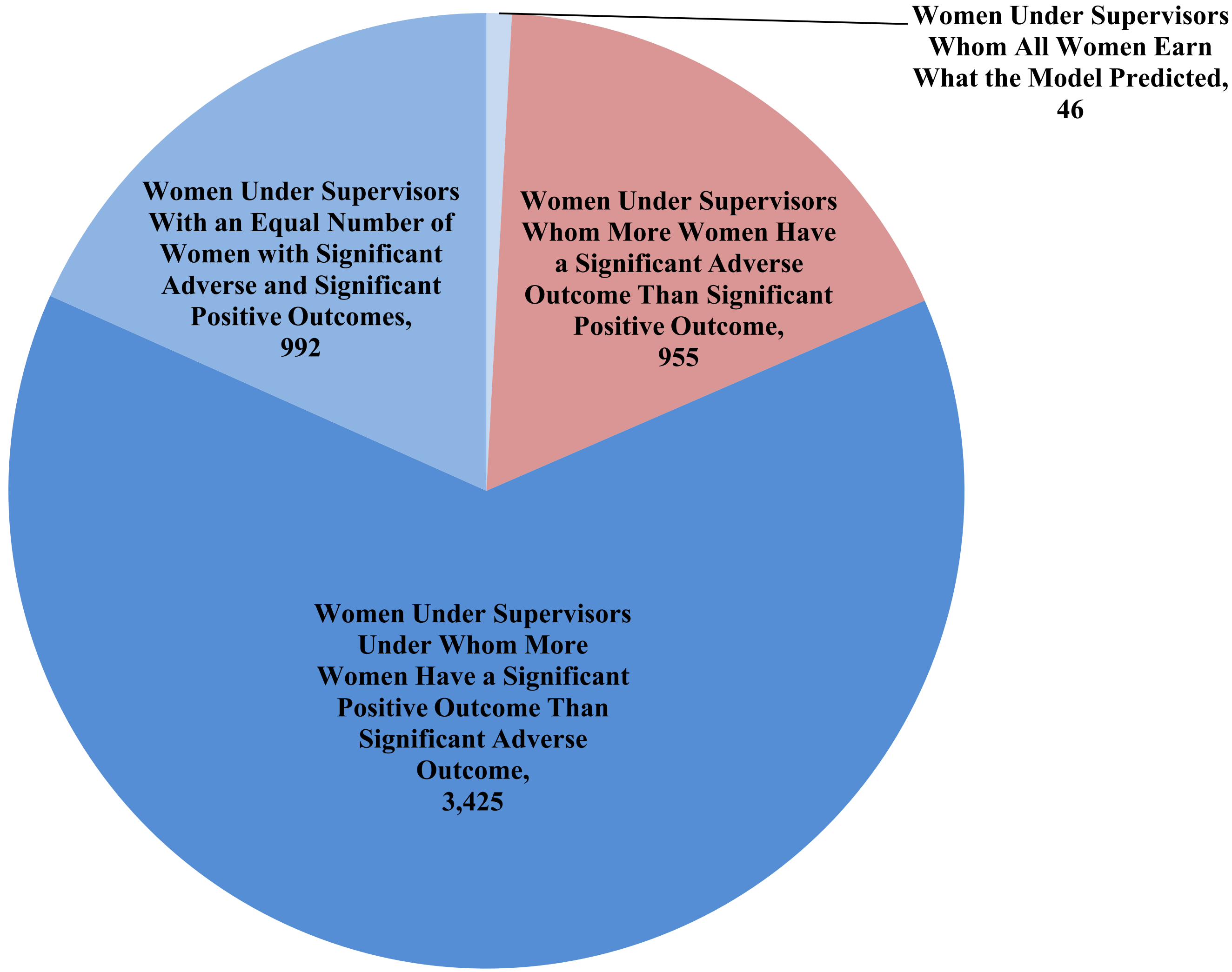
Level 2 Supervisors: Pay Outcomes for Women (Farber Model 5)
- Engineering & IT Operations, 2016 -



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 2 supervisors with at least 10 employees and accounts for 99% of female employees.

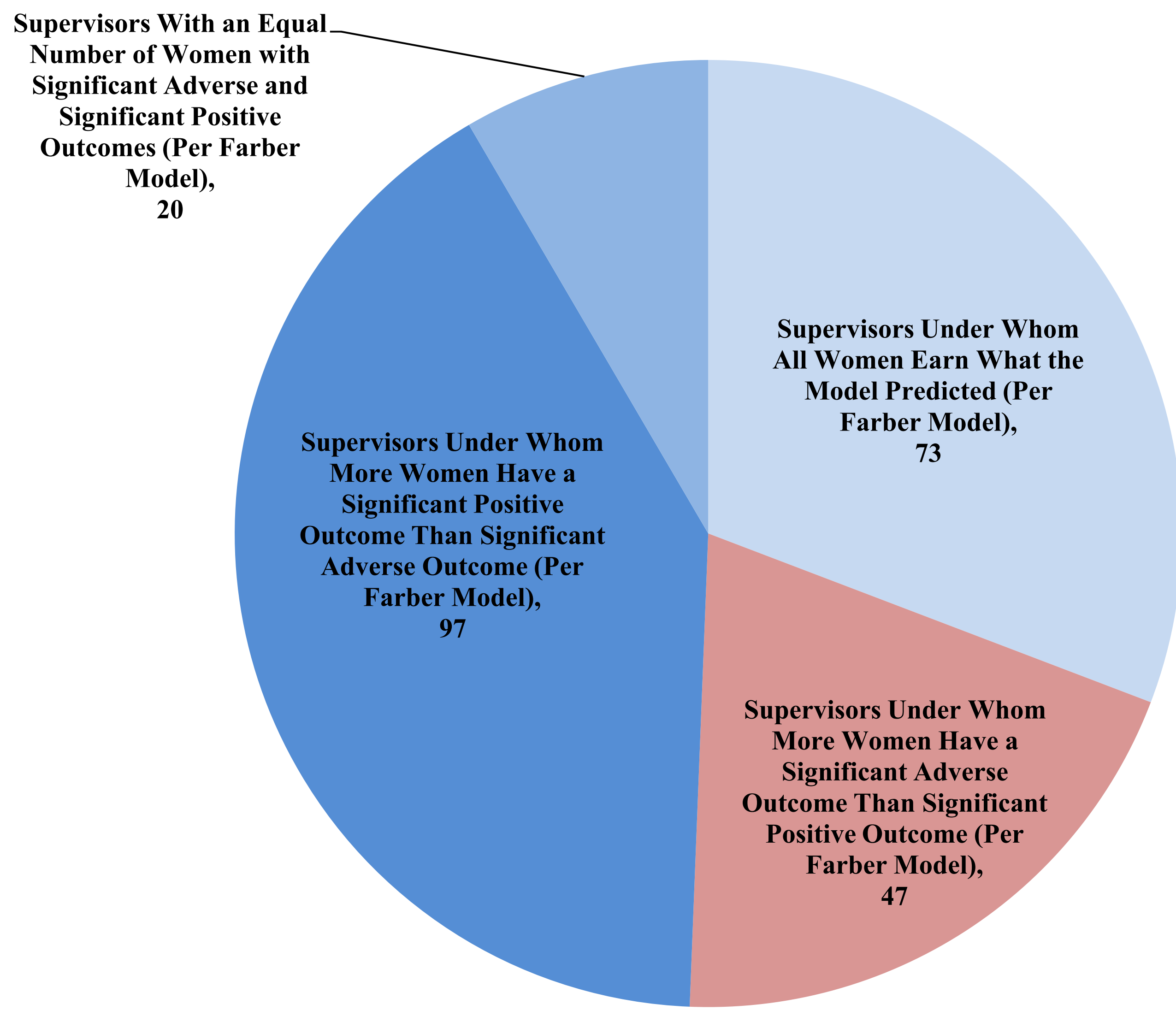
Pay Outcomes for Women By Level 2 Supervisor Category (Farber Model 5)

- Engineering & IT Operations, 2016 -



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 2 supervisors with at least 10 employees and accounts for 99% of female employees.

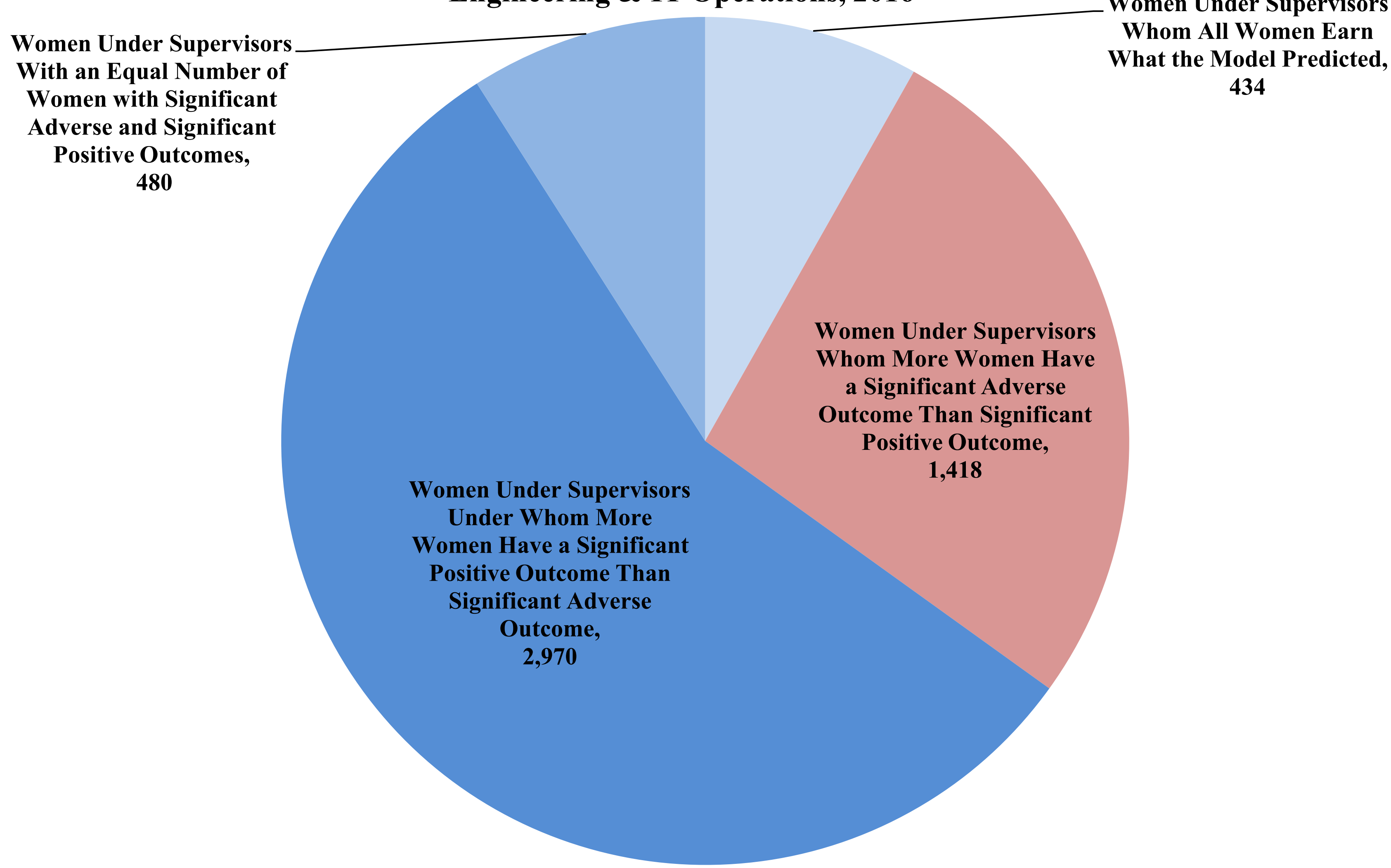
Level 3 Supervisors: Pay Outcomes for Women (Farber Model 5)
- Engineering & IT Operations, 2016 -



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 3 supervisors with at least 10 employees and accounts for 98% of female employees.

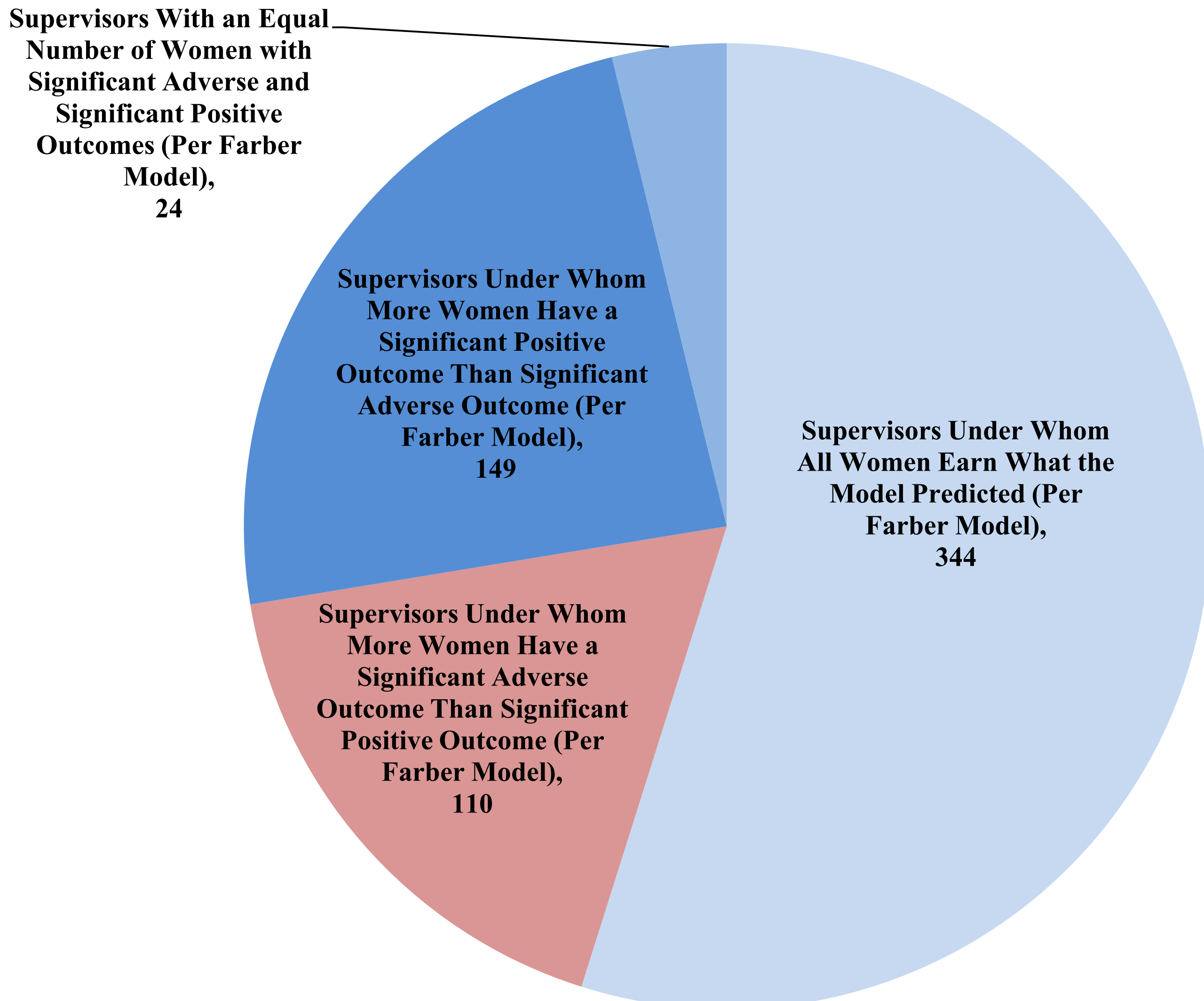
Pay Outcomes for Women By Level 3 Supervisor Category (Farber Model 5)

- Engineering & IT Operations, 2016 -



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 3 supervisors with at least 10 employees and accounts for 98% of female employees.

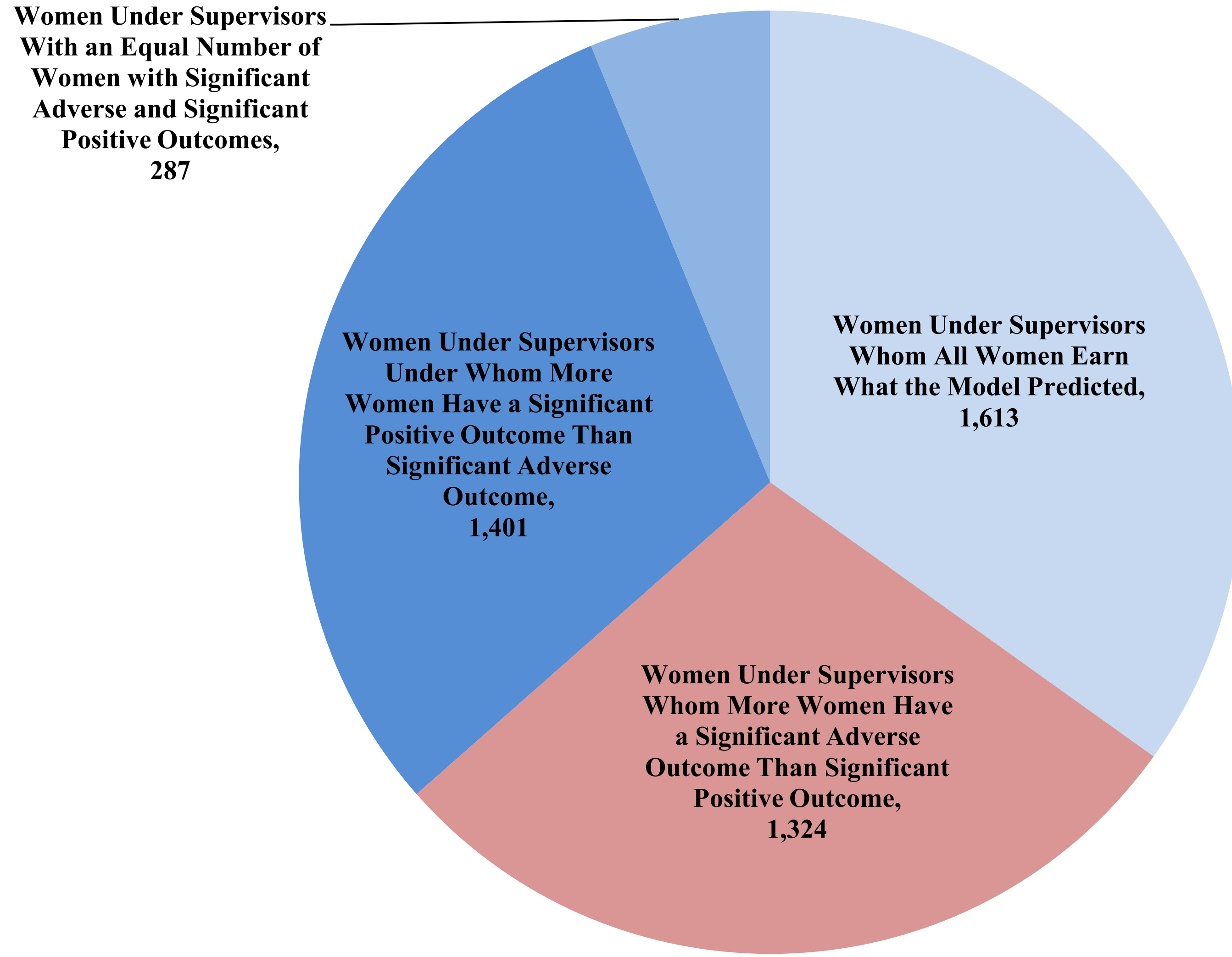
Level 4 Supervisors: Pay Outcomes for Women (Farber Model 5)
- Engineering & IT Operations, 2016 -



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 4 supervisors with at least 10 employees and accounts for 85% of female employees.

Pay Outcomes for Women By Level 4 Supervisor Category (Farber Model 5)

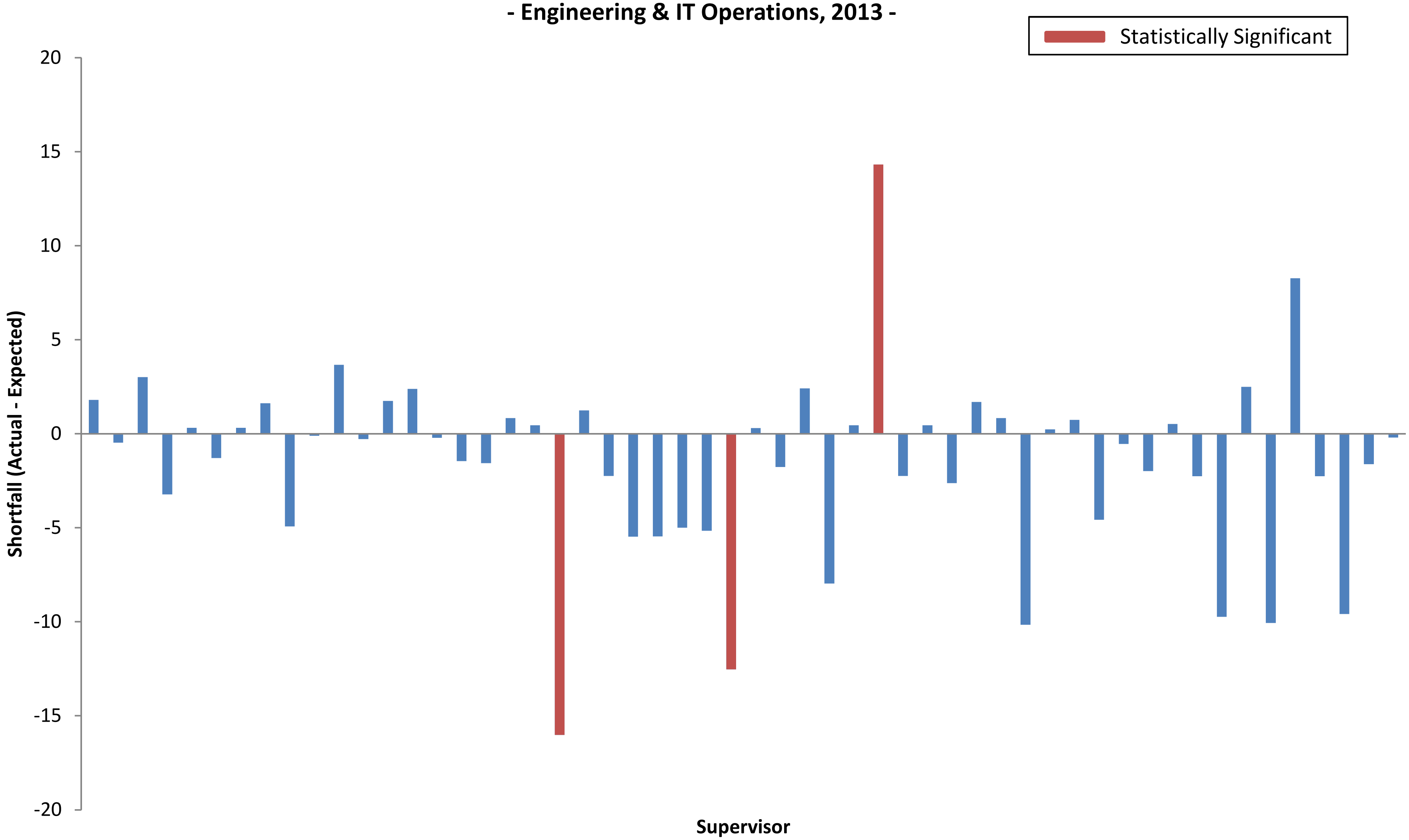
- Engineering & IT Operations, 2016 -



Note: Dr. Farber's pay Model 5 controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, and Standard Title. Chart is limited to Level 4 supervisors with at least 10 employees and accounts for 85% of female employees.

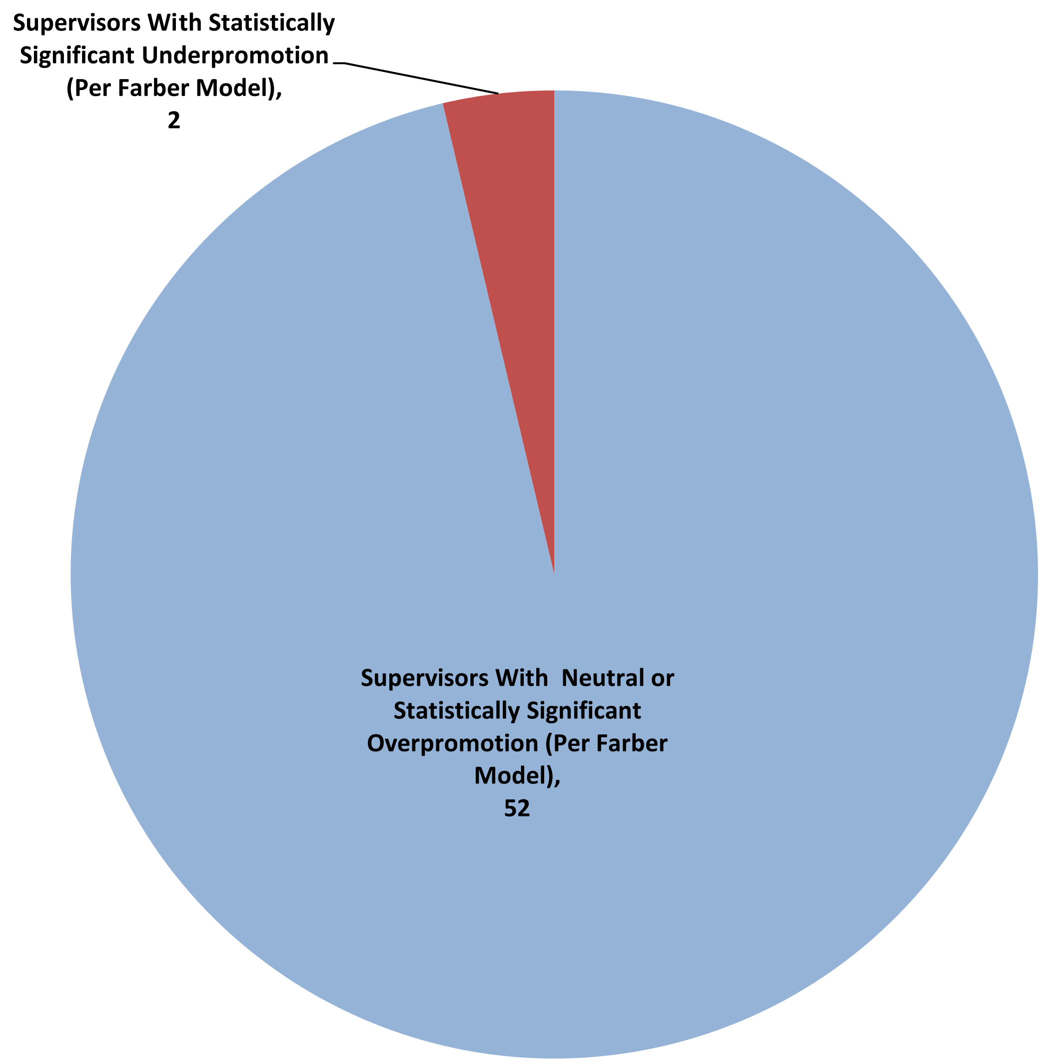
Dr. Farber's Promotion Model Shows Outcomes Among Women Vary Widely by Level 2 Supervisor: Some Supervisors Promote More Women Than Predicted and Others Promote Fewer

- Engineering & IT Operations, 2013 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 2 supervisors with at least 10 employees and accounts for 86% of female employees.

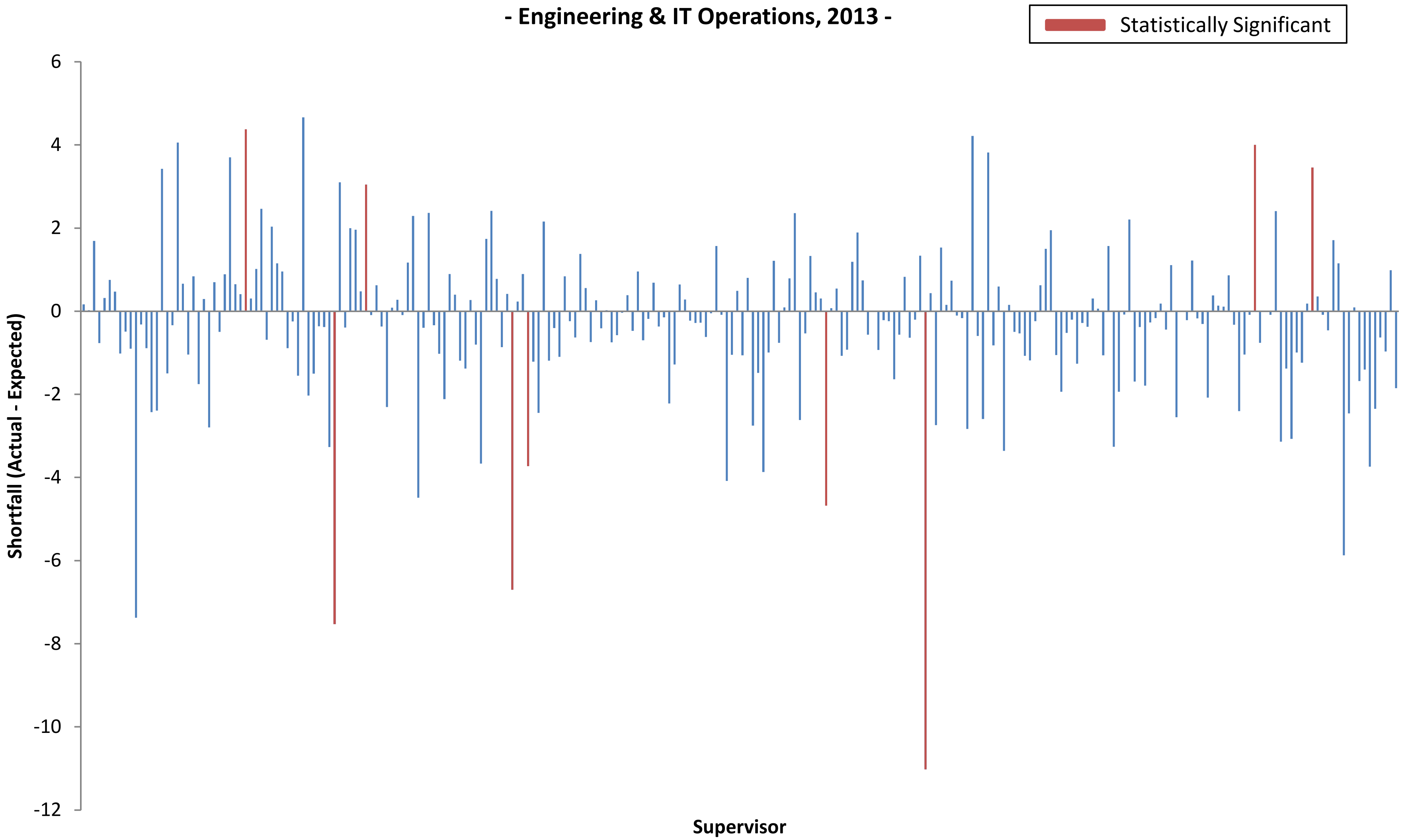
Level 2 Supervisors: Promotion Outcomes for Women
- Engineering & IT Operations, 2013 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 2 supervisors with at least 10 employees and accounts for 86% of female employees.

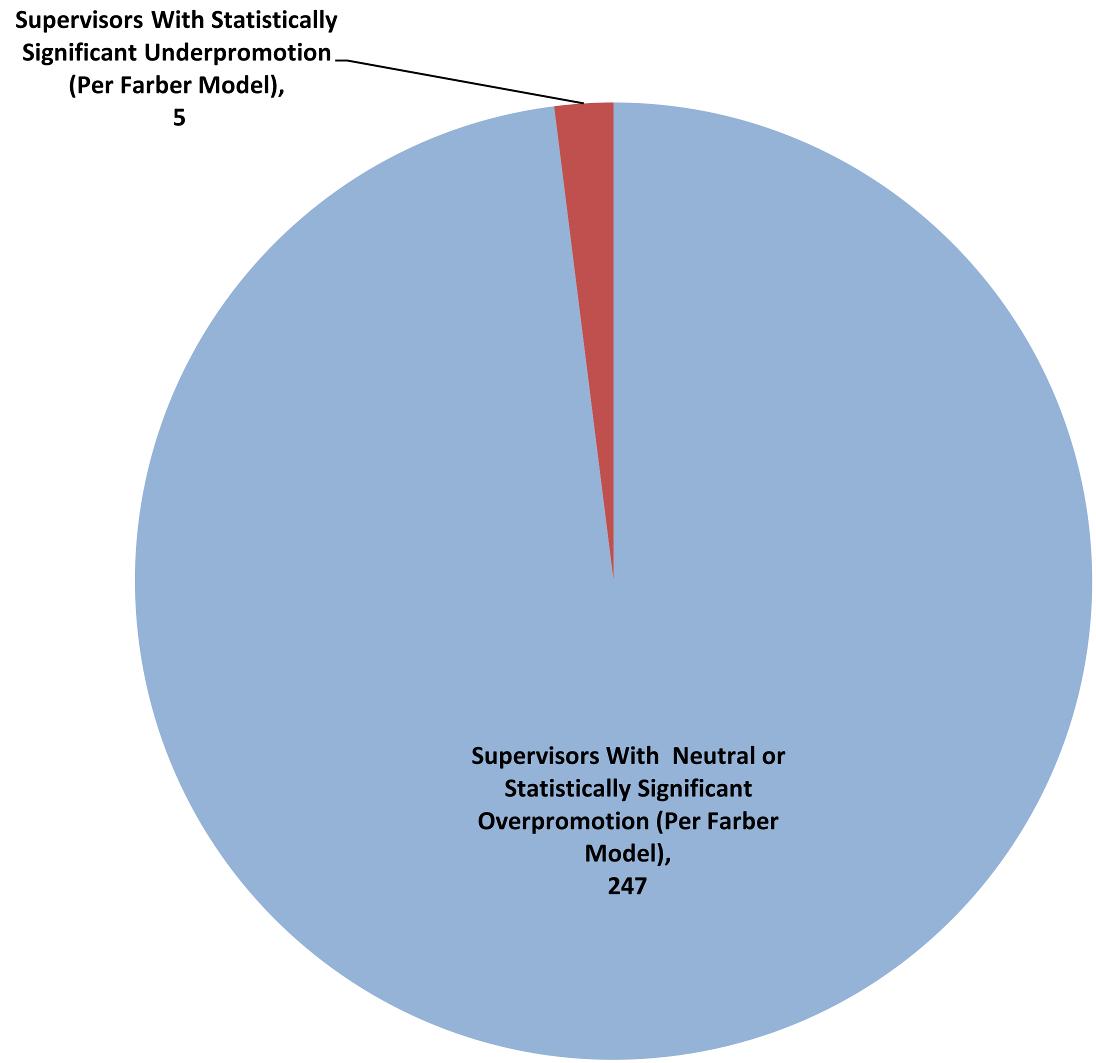
Dr. Farber's Promotion Model Shows Outcomes Among Women Vary Widely by Level 3 Supervisor: Some Supervisors Promote More Women Than Predicted and Others Promote Fewer

- Engineering & IT Operations, 2013 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 3 supervisors with at least 10 employees and accounts for 84% of female employees.

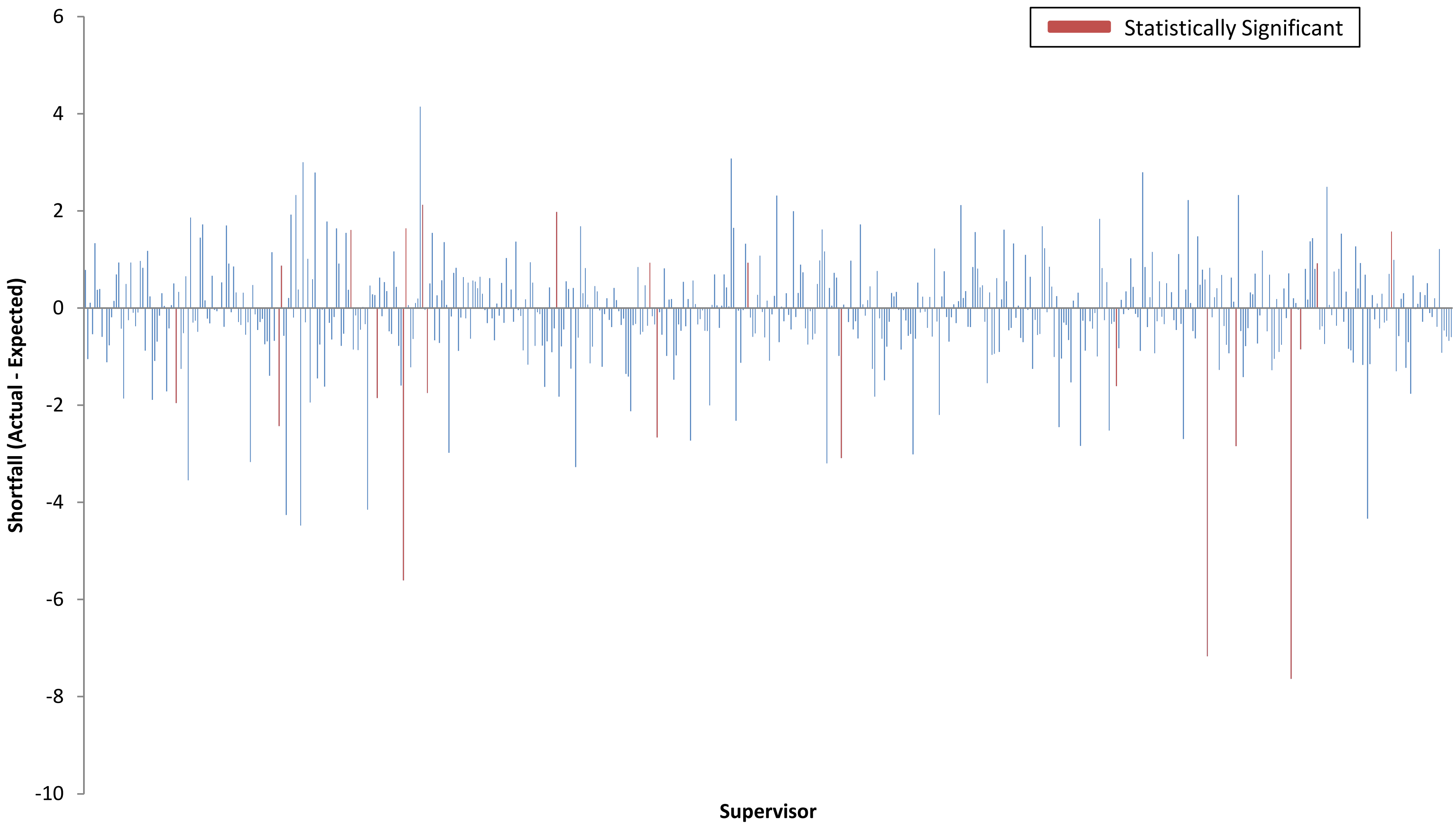
Level 3 Supervisors: Promotion Outcomes for Women
- Engineering & IT Operations, 2013 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 3 supervisors with at least 10 employees and accounts for 84% of female employees.

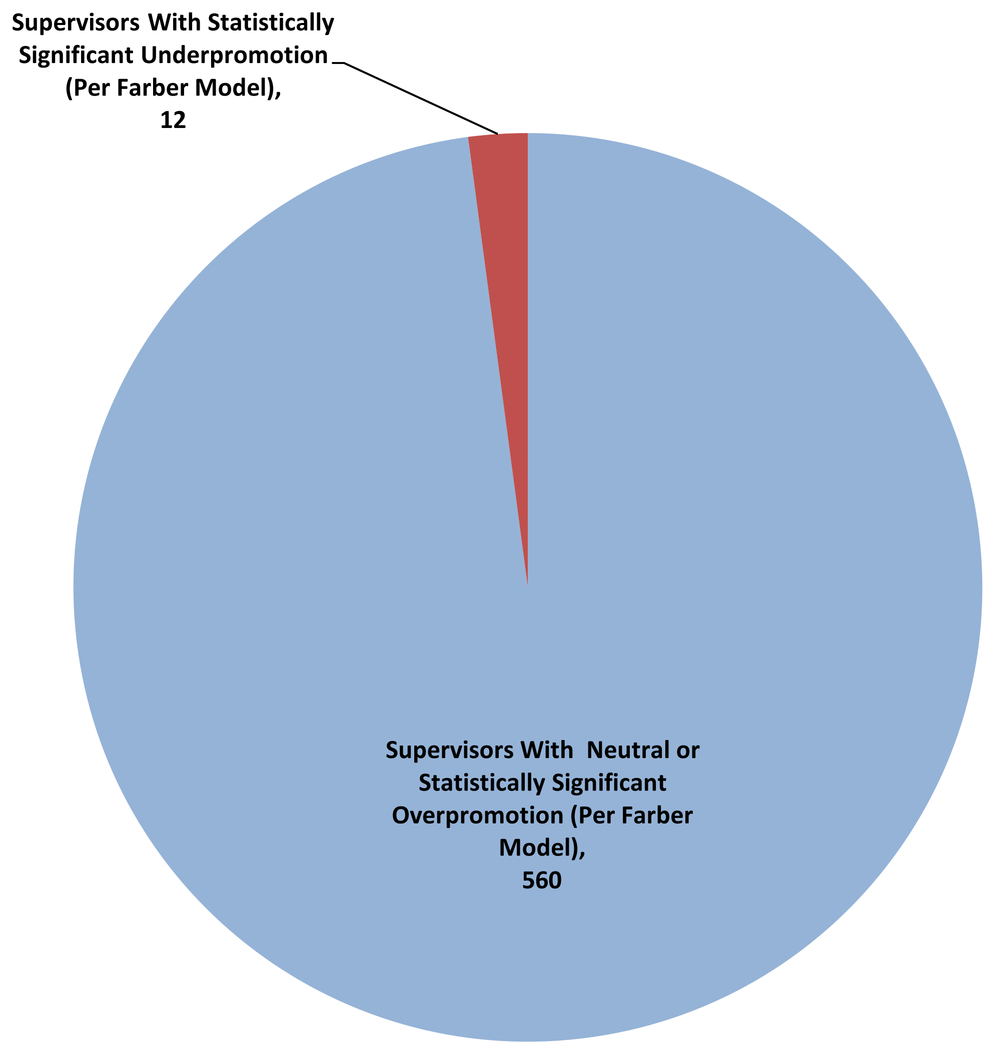
Dr. Farber's Promotion Model Shows Outcomes Among Women Vary Widely by Level 4 Supervisor: Some Supervisors Promote More Women Than Predicted and Others Promote Fewer

- Engineering & IT Operations, 2013 -

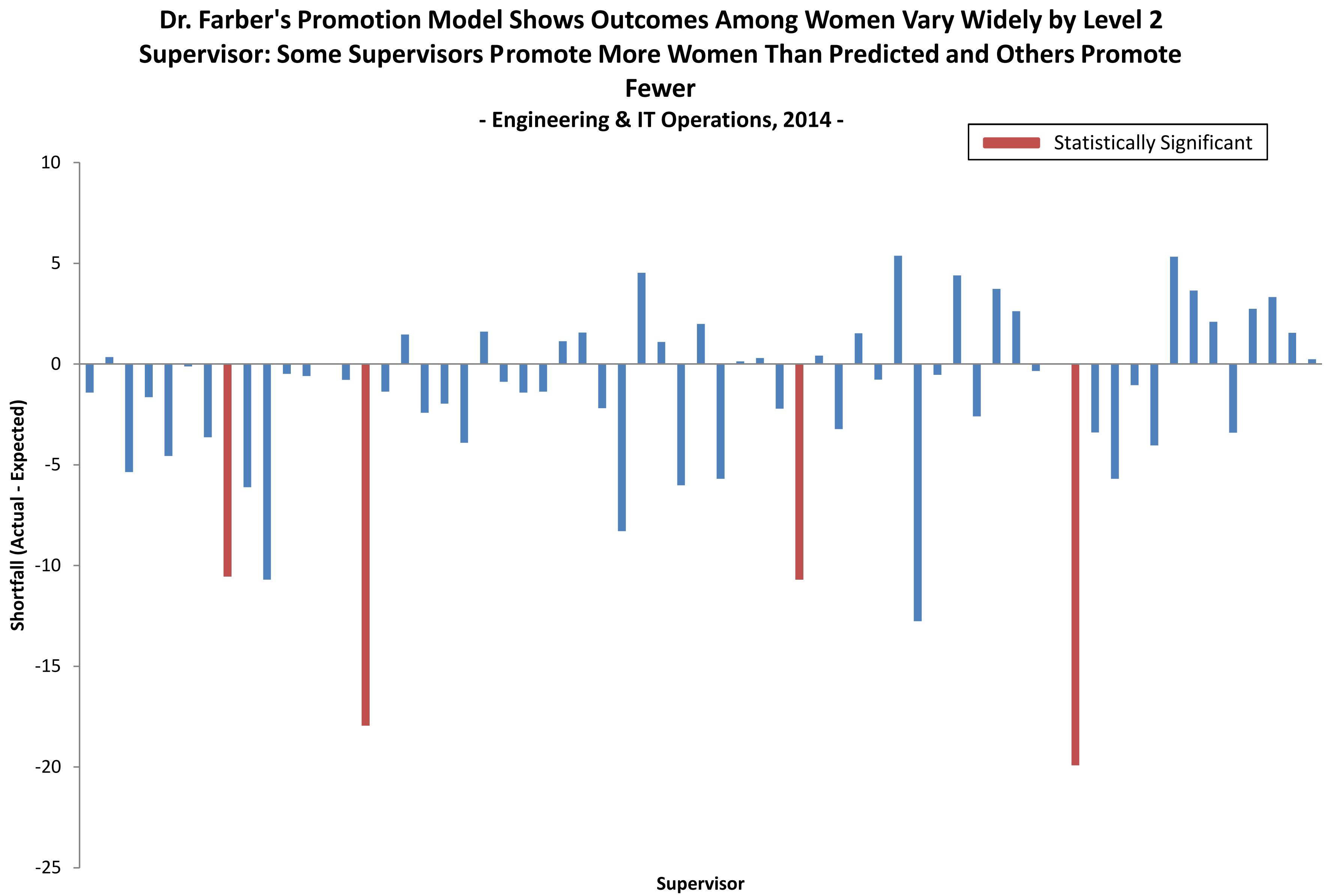


Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 4 supervisors with at least 10 employees and accounts for 68% of female employees.

Level 4 Supervisors: Promotion Outcomes for Women
- Engineering & IT Operations, 2013 -

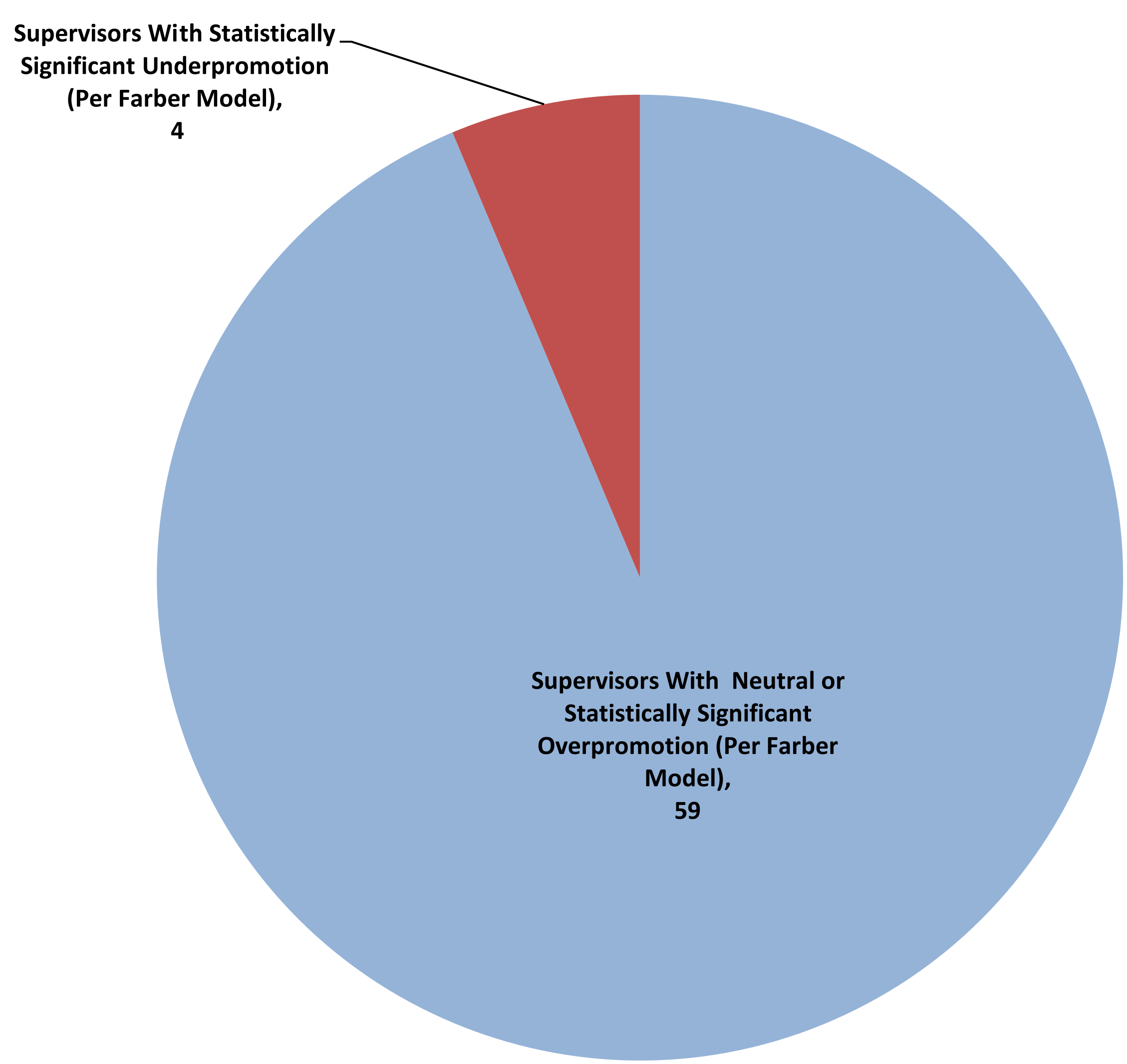


Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 4 supervisors with at least 10 employees and accounts for 68% of female employees.



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. 7% of female employees have an "Open Position" Level 2 supervisor, which is excluded from the chart.. Chart is limited to Level 2 supervisors with at least 10 employees and accounts for 90% of female employees.

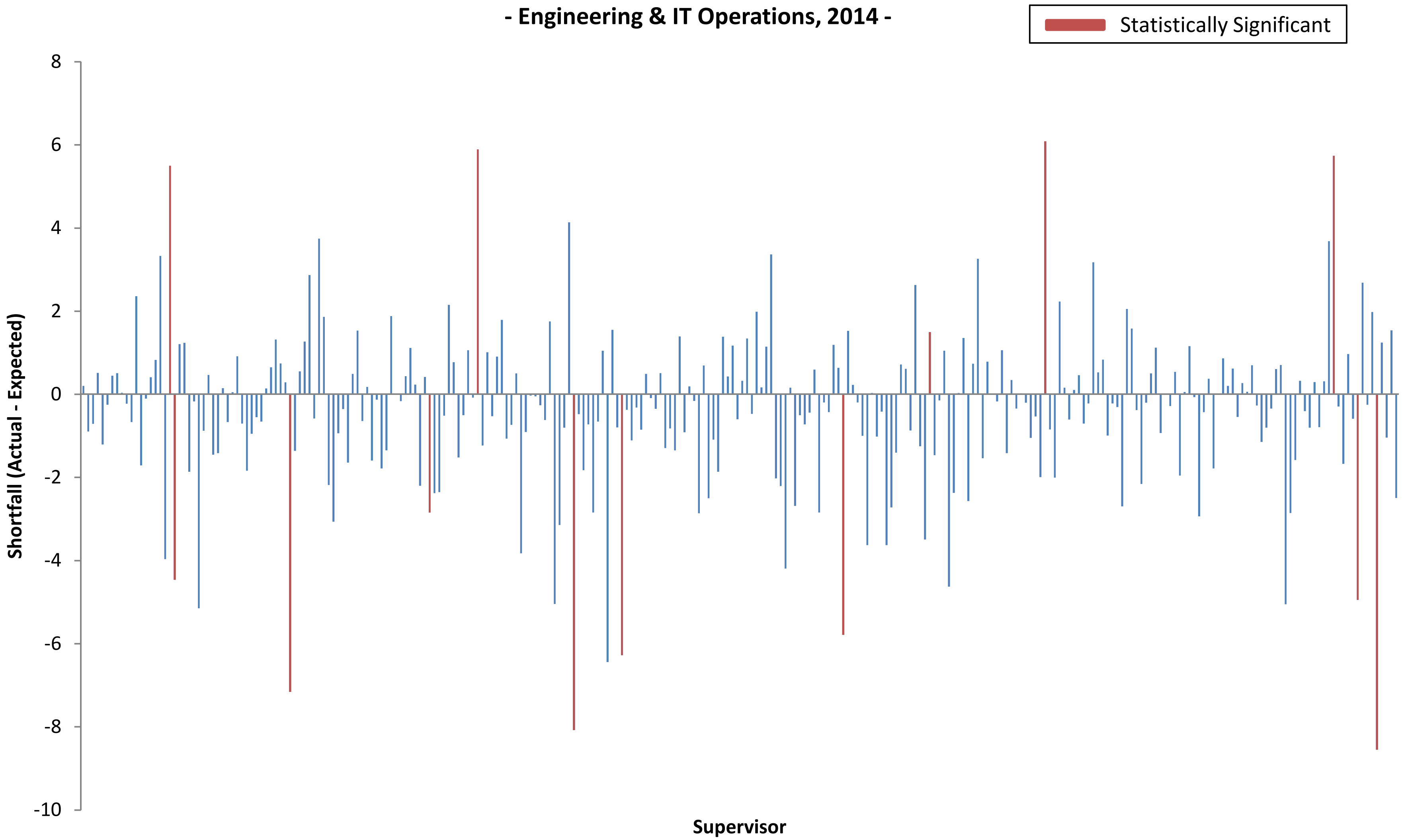
Level 2 Supervisors: Promotion Outcomes for Women
- Engineering & IT Operations, 2014 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. 7% of female employees have an "Open Position" Level 2 supervisor, which is excluded from the chart. Chart is limited to Level 2 supervisors with at least 10 employees and accounts for 90% of female employees.

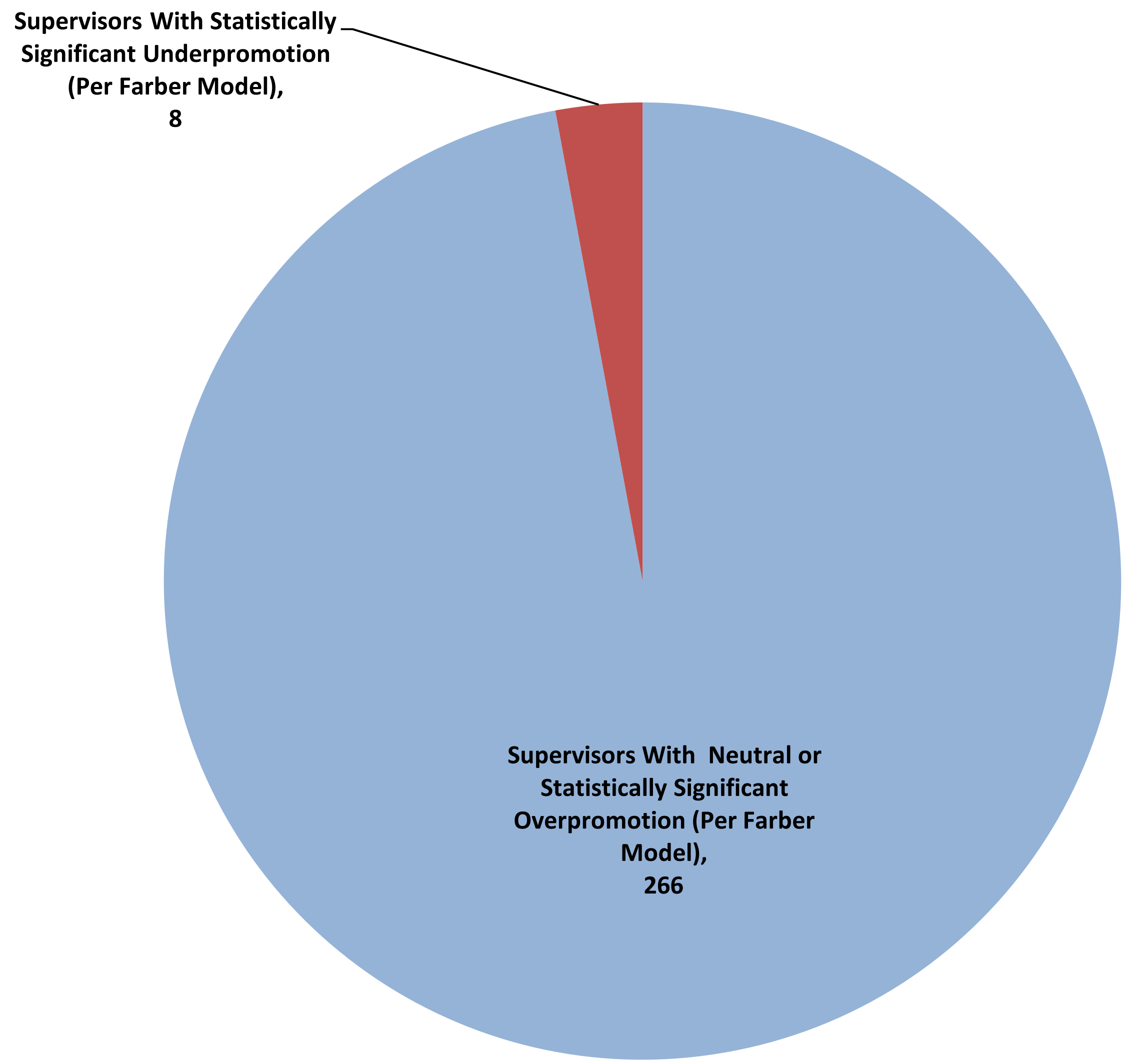
Dr. Farber's Promotion Model Shows Outcomes Among Women Vary Widely by Level 3 Supervisor: Some Supervisors Promote More Women Than Predicted and Others Promote Fewer

- Engineering & IT Operations, 2014 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 3 supervisors with at least 10 employees and accounts for 95% of female employees.

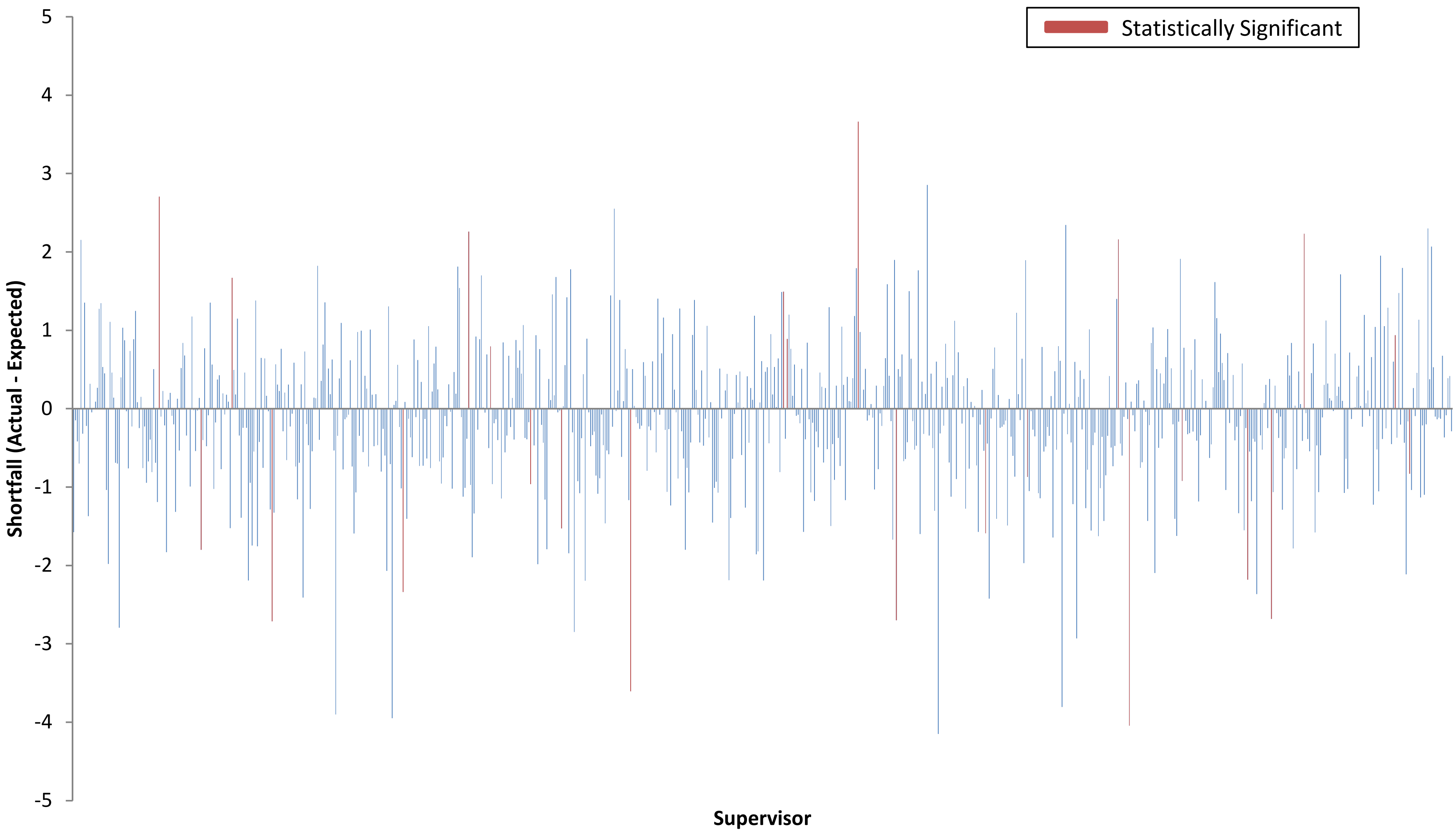
Level 3 Supervisors: Promotion Outcomes for Women
- Engineering & IT Operations, 2014 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 3 supervisors with at least 10 employees and accounts for 95% of female employees.

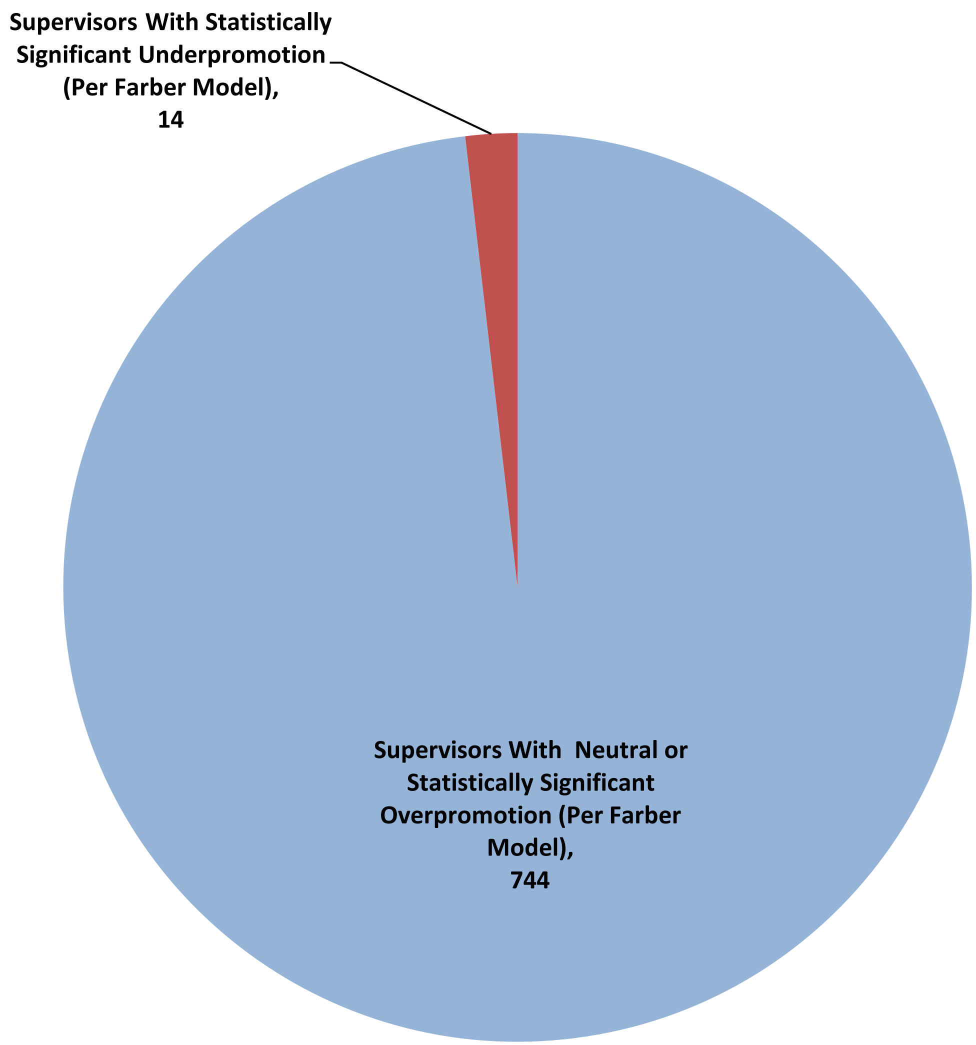
Dr. Farber's Promotion Model Shows Outcomes Among Women Vary Widely by Level 4 Supervisor: Some Supervisors Promote More Women Than Predicted and Others Promote Fewer

- Engineering & IT Operations, 2014 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 4 supervisors with at least 10 employees and accounts for 80% of female employees.

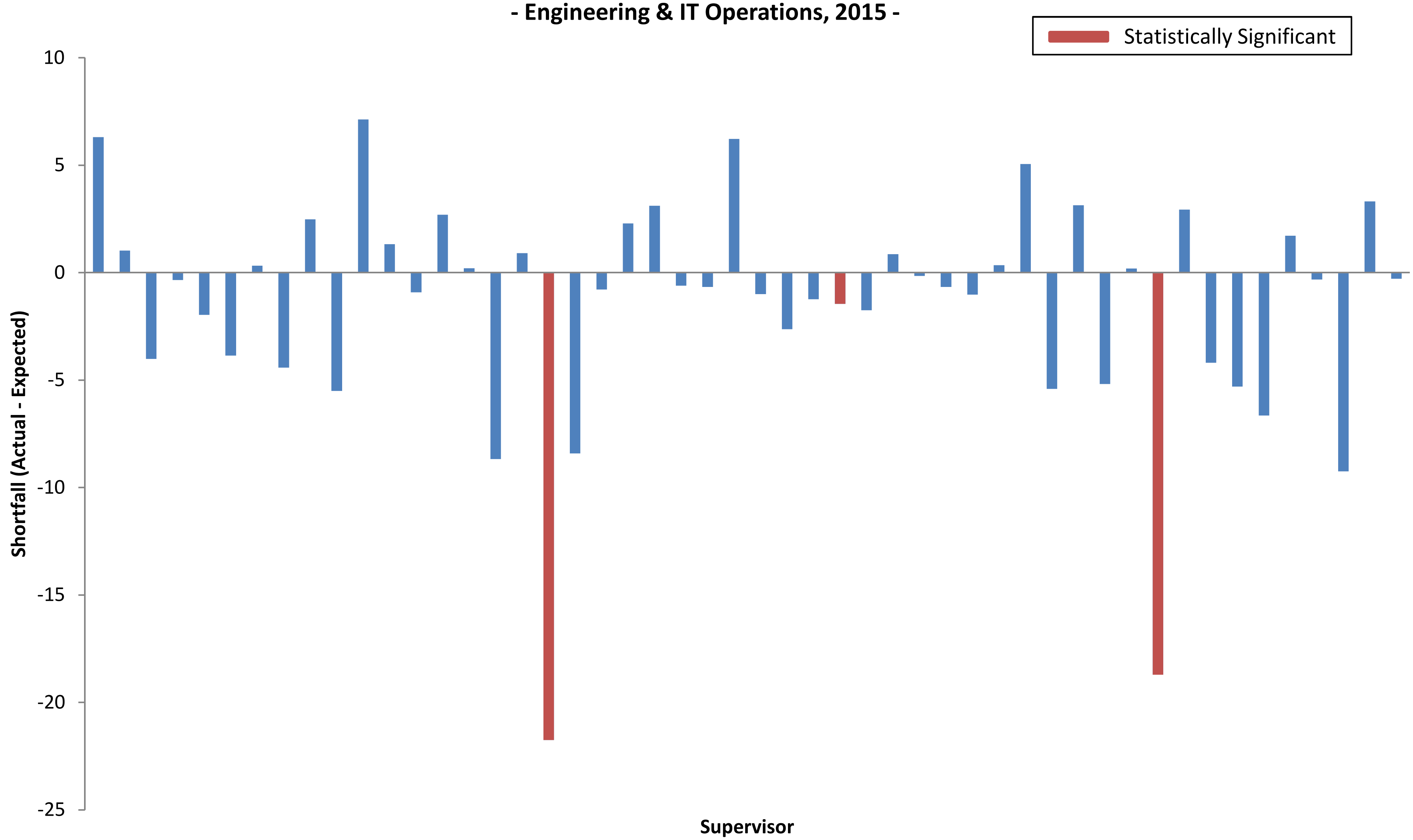
Level 4 Supervisors: Promotion Outcomes for Women
- Engineering & IT Operations, 2014 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 4 supervisors with at least 10 employees and accounts for 80% of female employees.

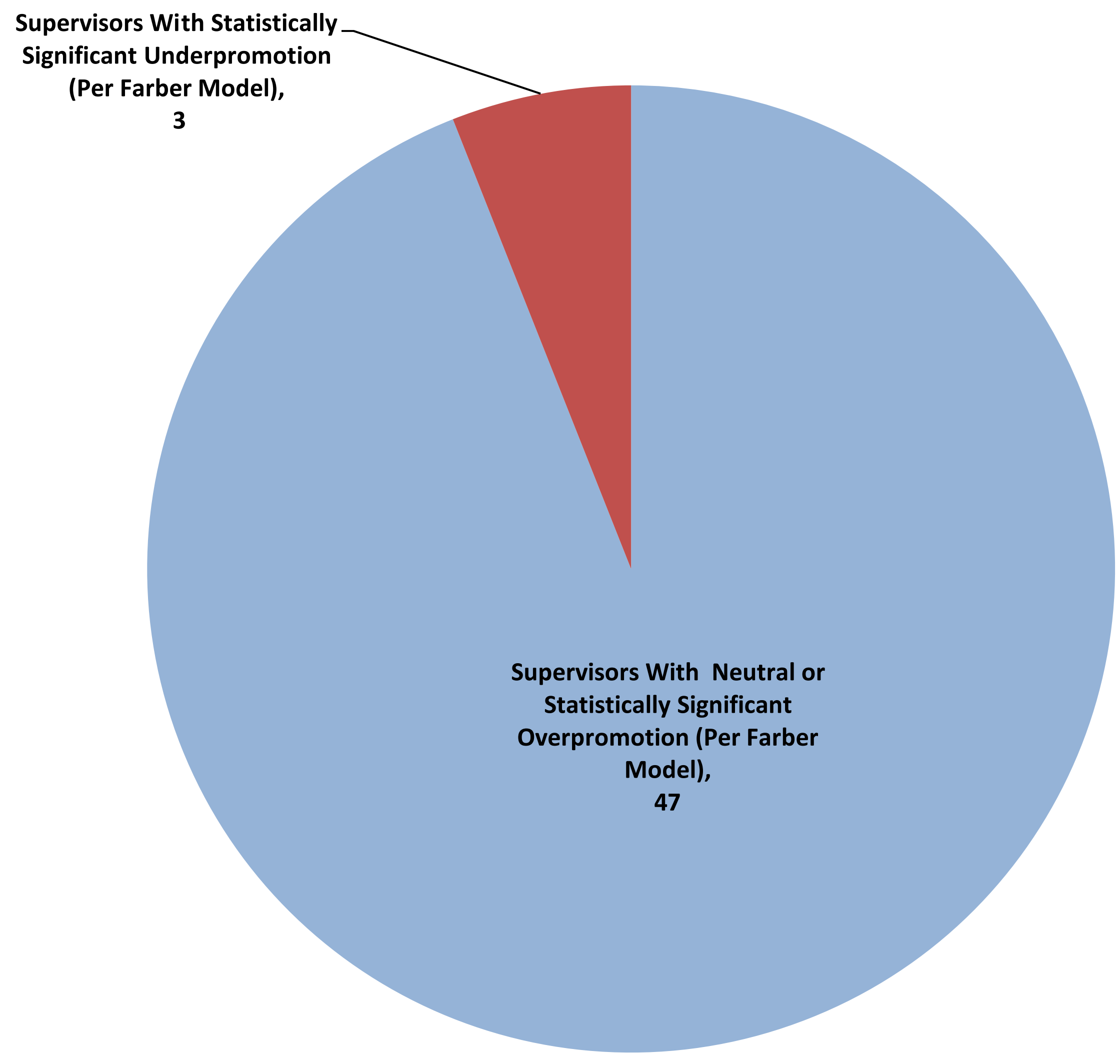
Dr. Farber's Promotion Model Shows Outcomes Among Women Vary Widely by Level 2 Supervisor: Some Supervisors Promote More Women Than Predicted and Others Promote Fewer

- Engineering & IT Operations, 2015 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 2 supervisors with at least 10 employees and accounts for 99% of female employees.

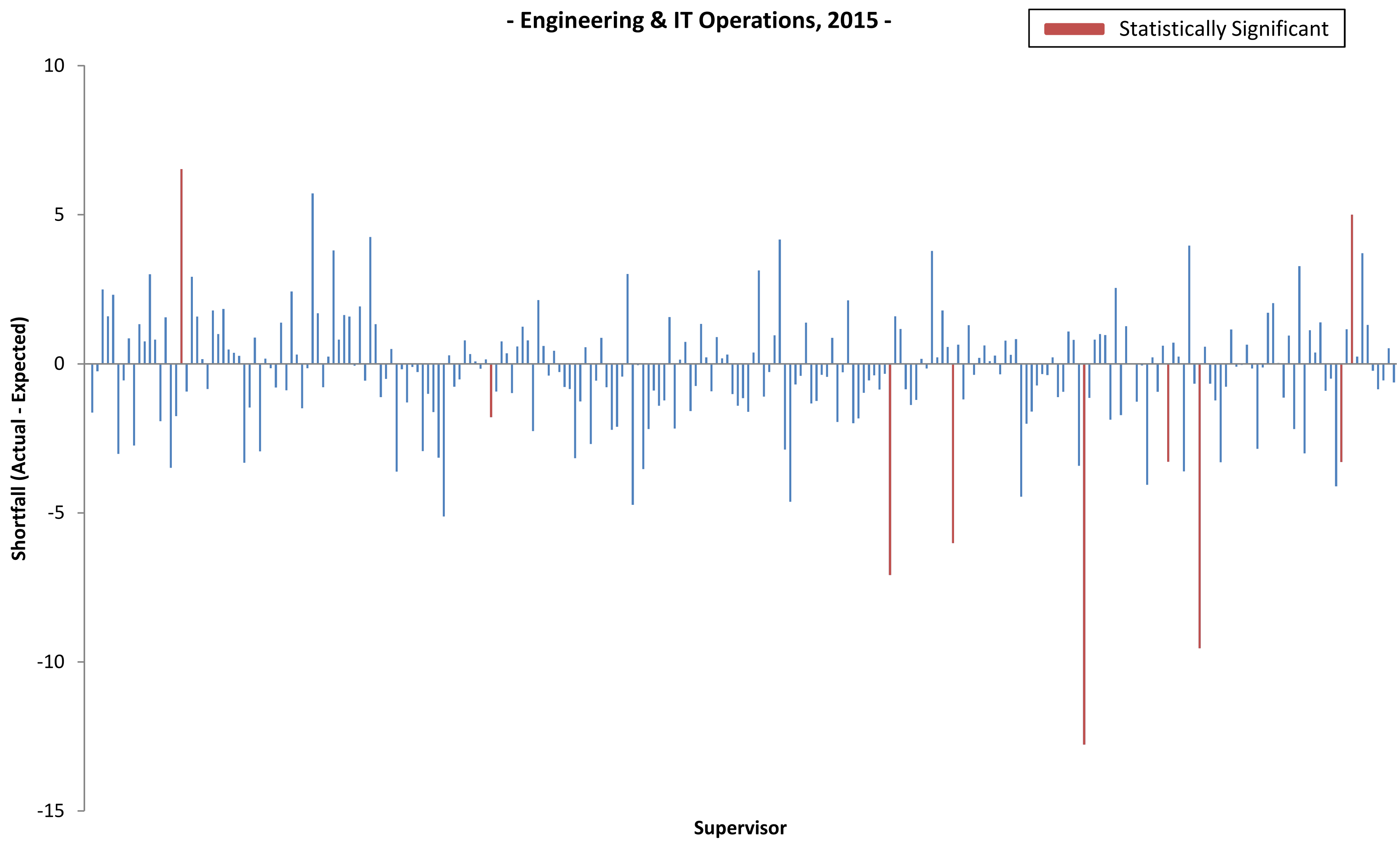
Level 2 Supervisors: Promotion Outcomes for Women
- Engineering & IT Operations, 2015 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 2 supervisors with at least 10 employees and accounts for 99% of female employees.

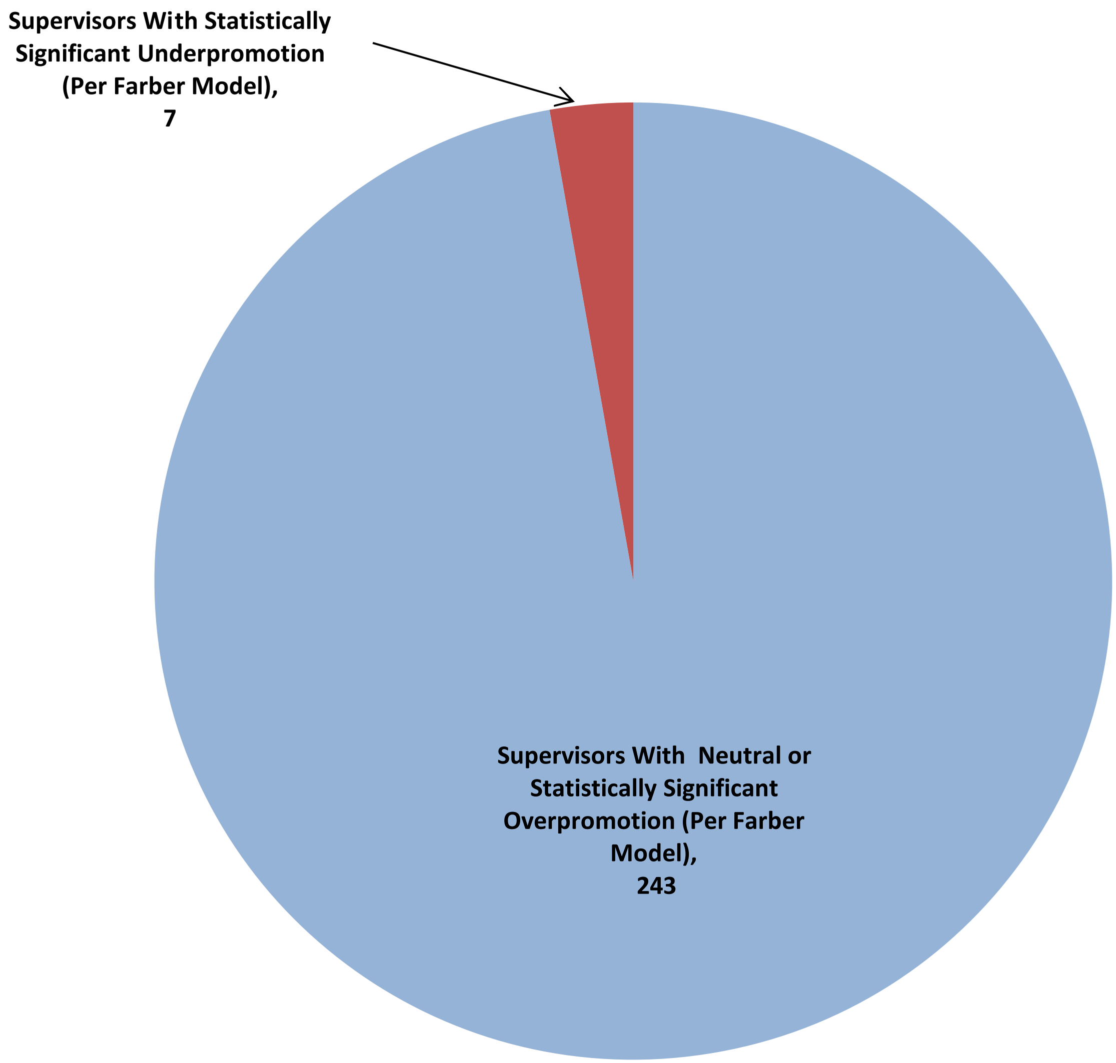
Dr. Farber's Promotion Model Shows Outcomes Among Women Vary Widely by Level 3 Supervisor: Some Supervisors Promote More Women Than Predicted and Others Promote Fewer

- Engineering & IT Operations, 2015 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 3 supervisors with at least 10 employees and accounts for 97% of female employees.

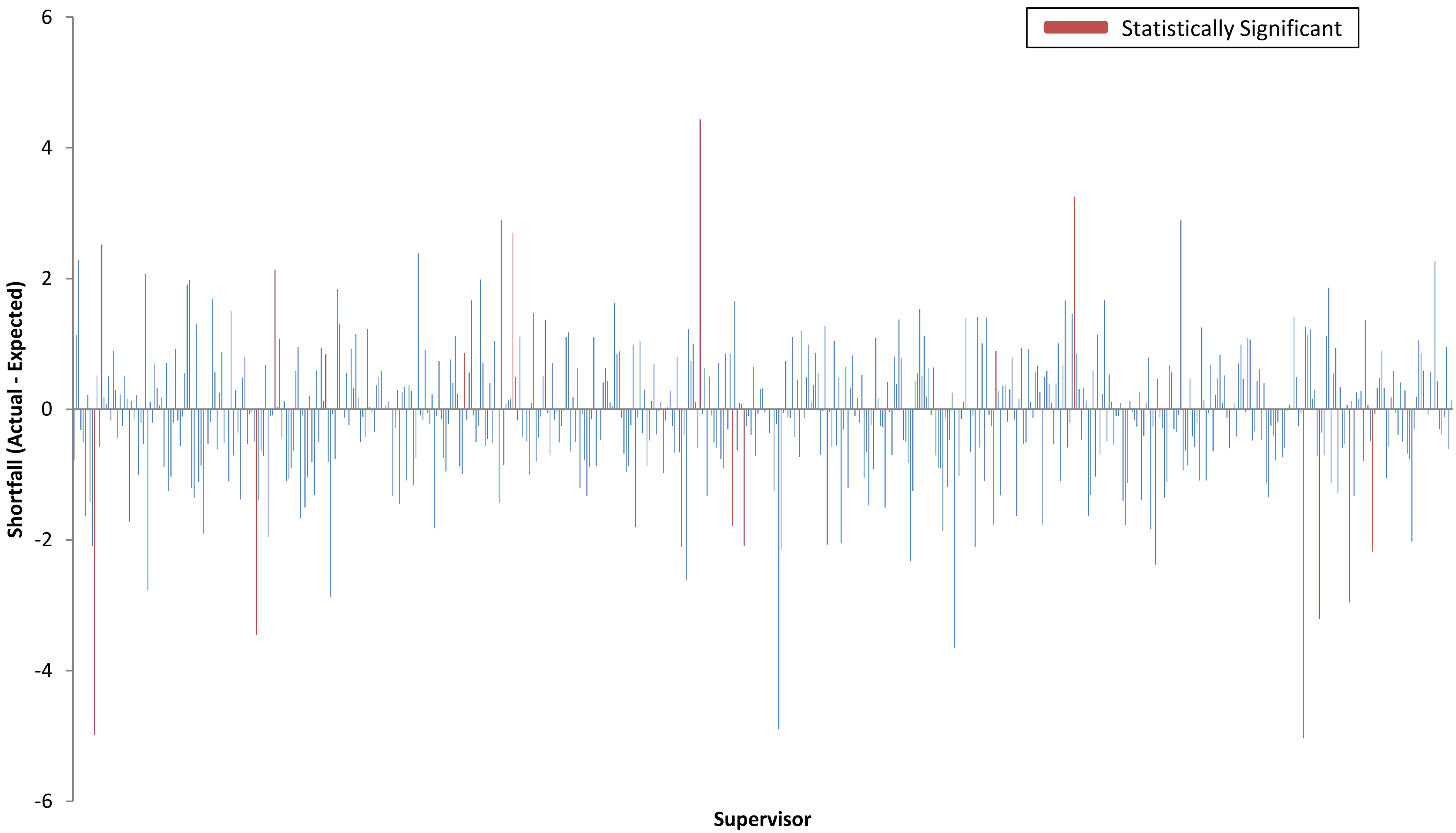
Level 3 Supervisors: Promotion Outcomes for Women
- Engineering & IT Operations, 2015 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 3 supervisors with at least 10 employees and accounts for 97% of female employees.

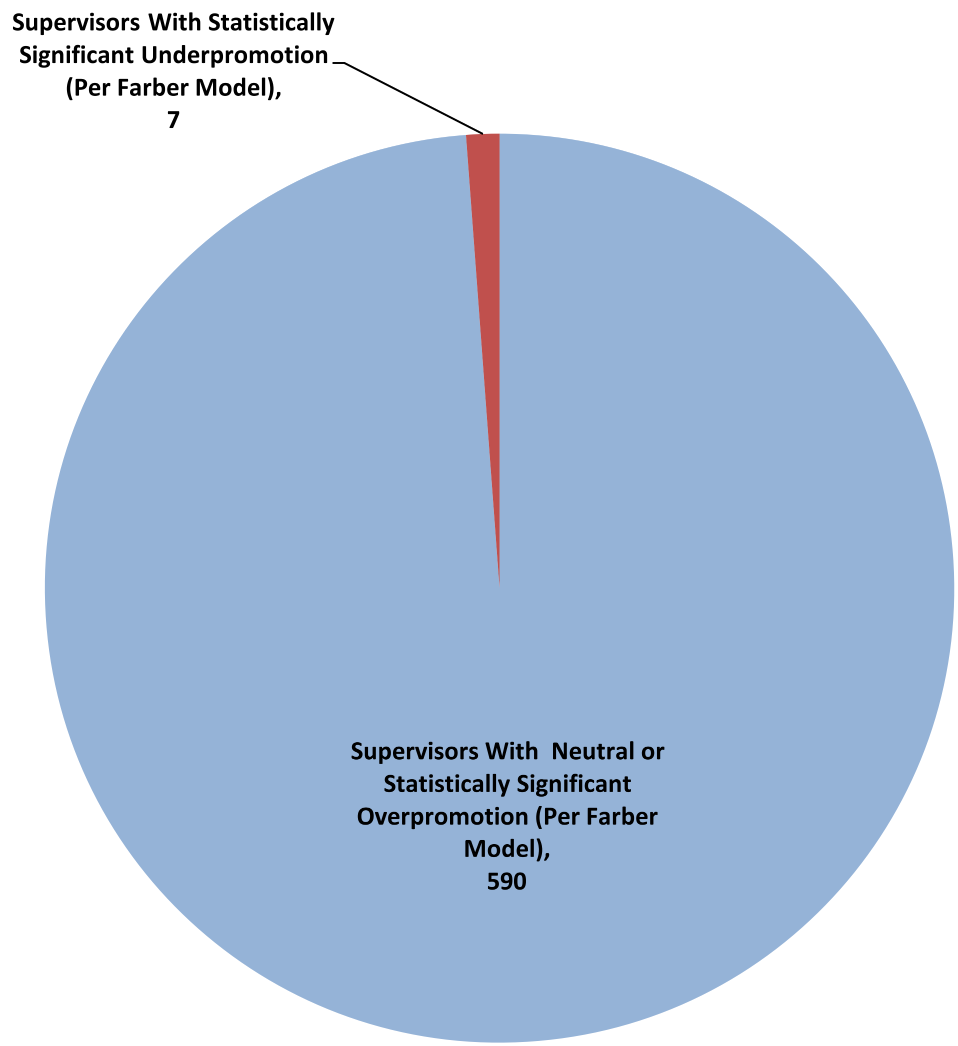
Dr. Farber's Promotion Model Shows Outcomes Among Women Vary Widely by Level 4 Supervisor: Some Supervisors Promote More Women Than Predicted and Others Promote Fewer

- Engineering & IT Operations, 2015 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 4 supervisors with at least 10 employees and accounts for 78% of female employees.

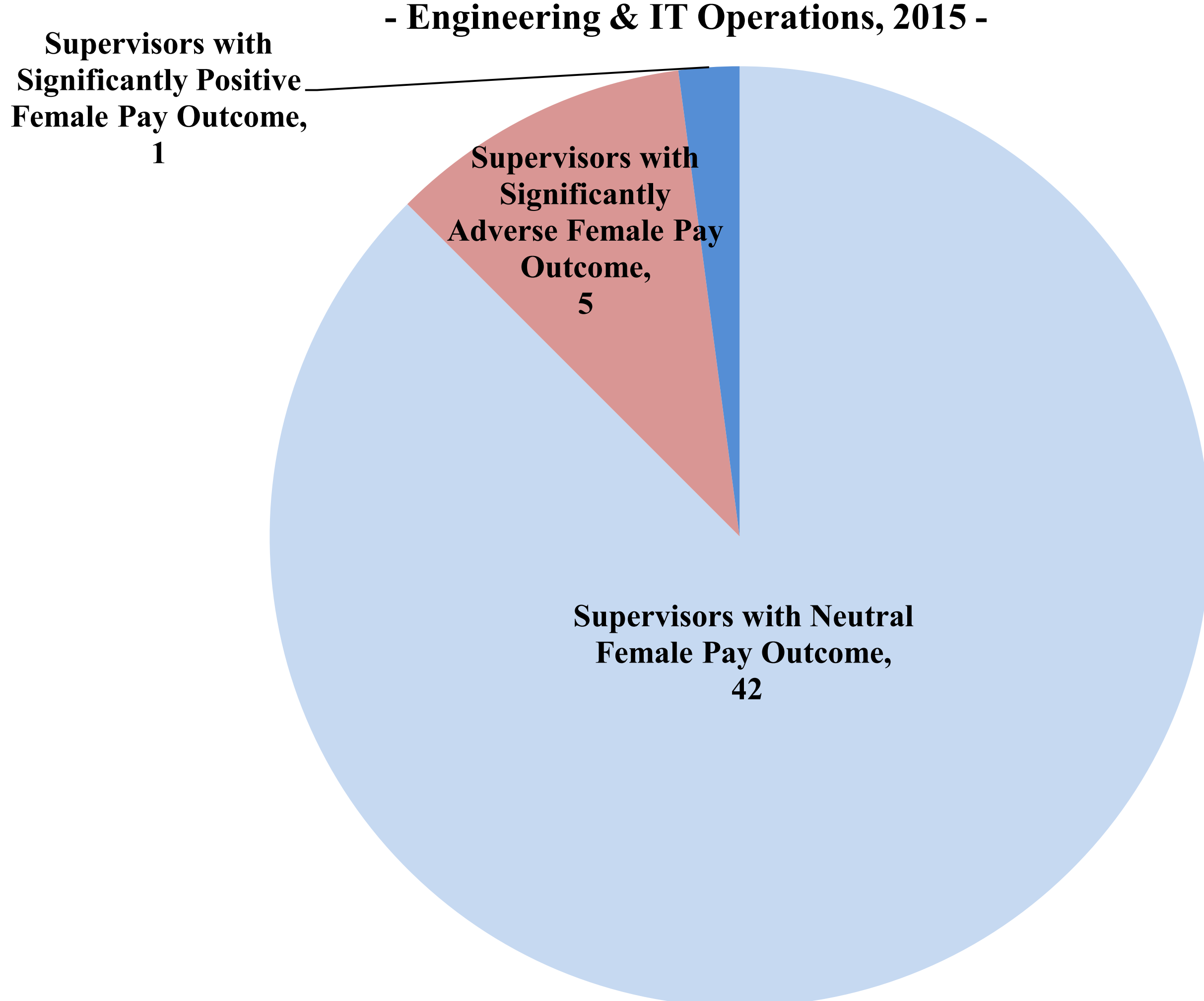
Level 4 Supervisors: Promotion Outcomes for Women
- Engineering & IT Operations, 2015 -



Note: Dr. Farber's probit model of Stock Level advancement controls for tenure, age, year, performance, location, Discipline, and prior Stock Level and is estimated for men only. Chart is limited to Level 4 supervisors with at least 10 employees and accounts for 78% of female employees.

Level 2 Supervisors: Pay Outcomes for Women (Farber Model 5 with Stock Level)

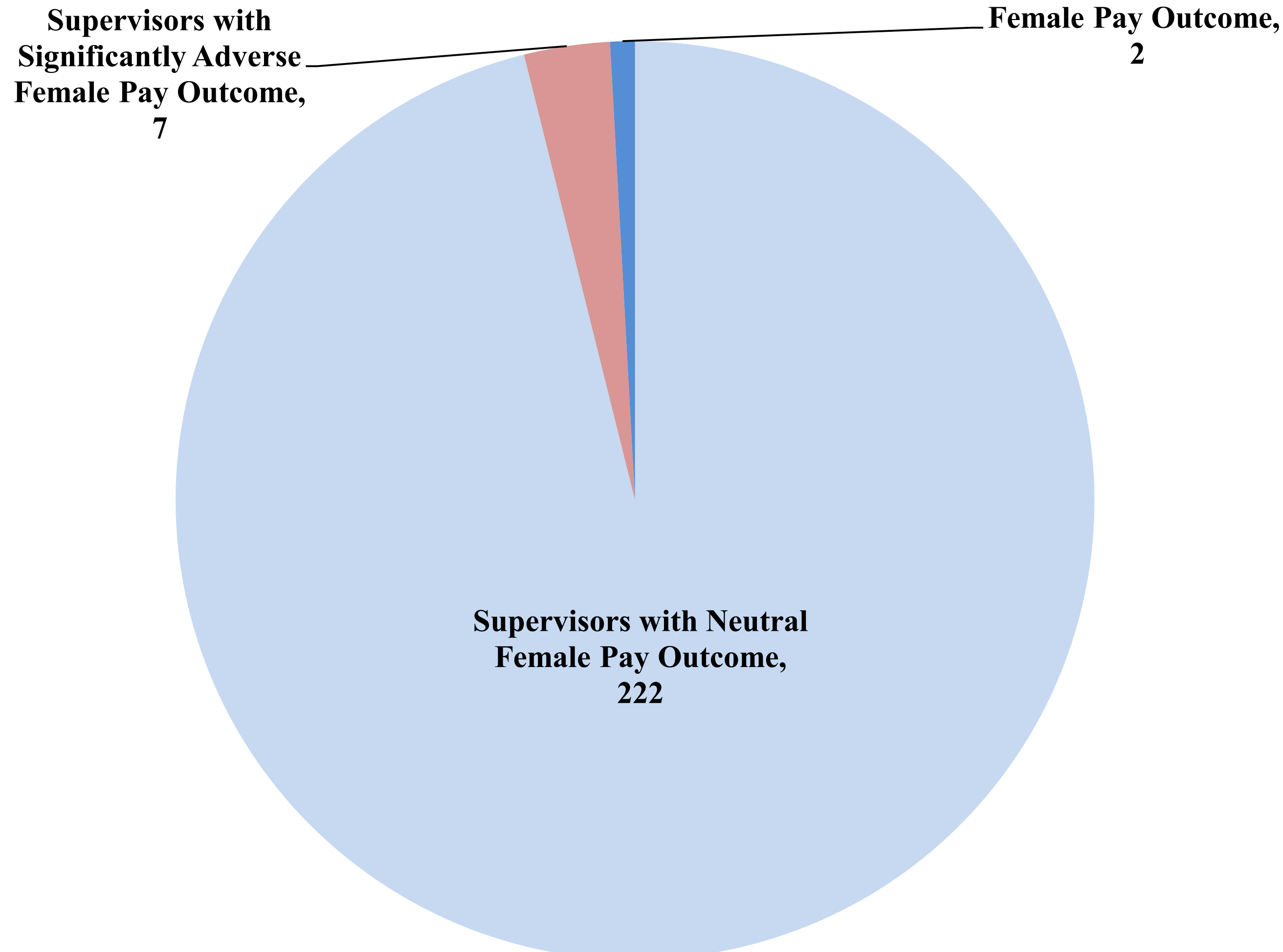
- Engineering & IT Operations, 2015 -



Note: Dr. Farber's pay Model 5 with Stock Level controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, Standard Title, and Stock Level. Analysis is limited to 48 out of 77 supervisors for whom the female coefficient and T-statistic can be calculated which accounts for 99% of women. 84% of women are under supervisors with neutral or significantly positive female pay outcome. 90% of women work in groups of 300 or more.

Level 3 Supervisors: Pay Outcomes for Women (Farber Model 5 with Stock Level)

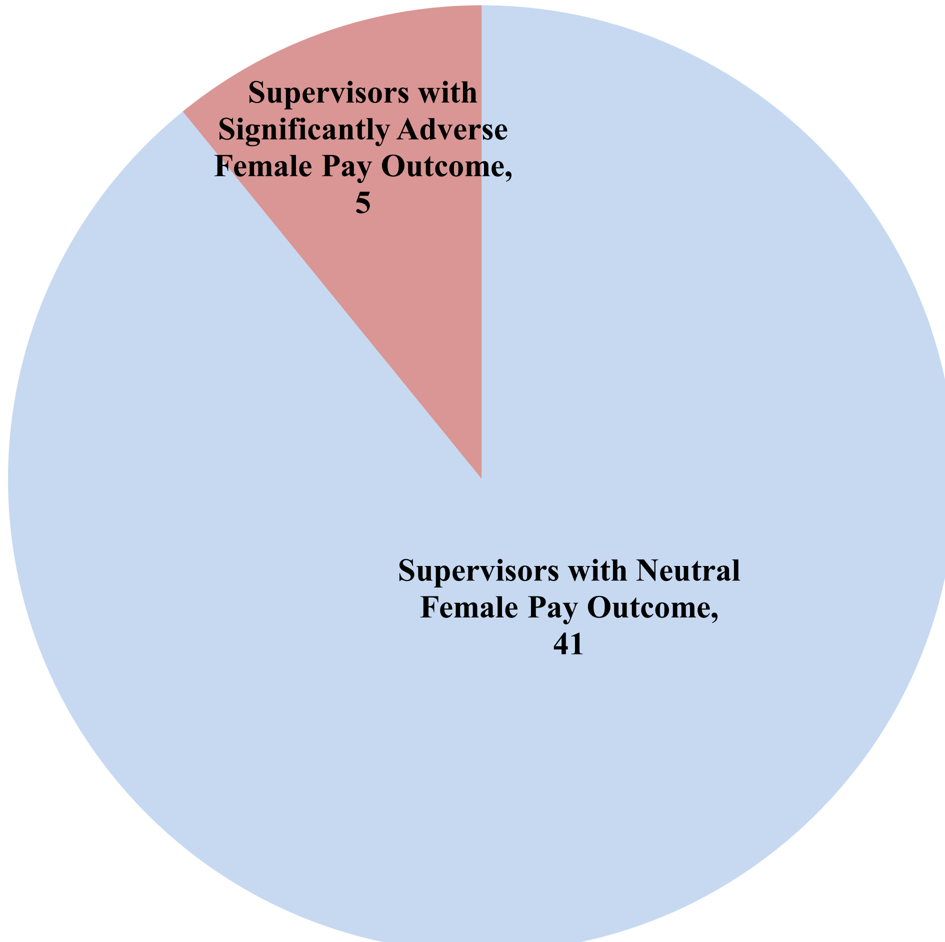
- Engineering & IT Operations, 2015 -



Note: Dr. Farber's pay Model 5 with Stock Level controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, Standard Title, and Stock Level. Analysis is limited to 231 out of 446 supervisors for whom the female coefficient and T-statistic can be calculated which accounts for 96% of women. 94% of women are under supervisors with neutral or significantly positive female pay outcome. 38% of women work in groups of 300 or more.

Level 2 Supervisors: Pay Outcomes for Women (Farber Model 5 with Stock Level)

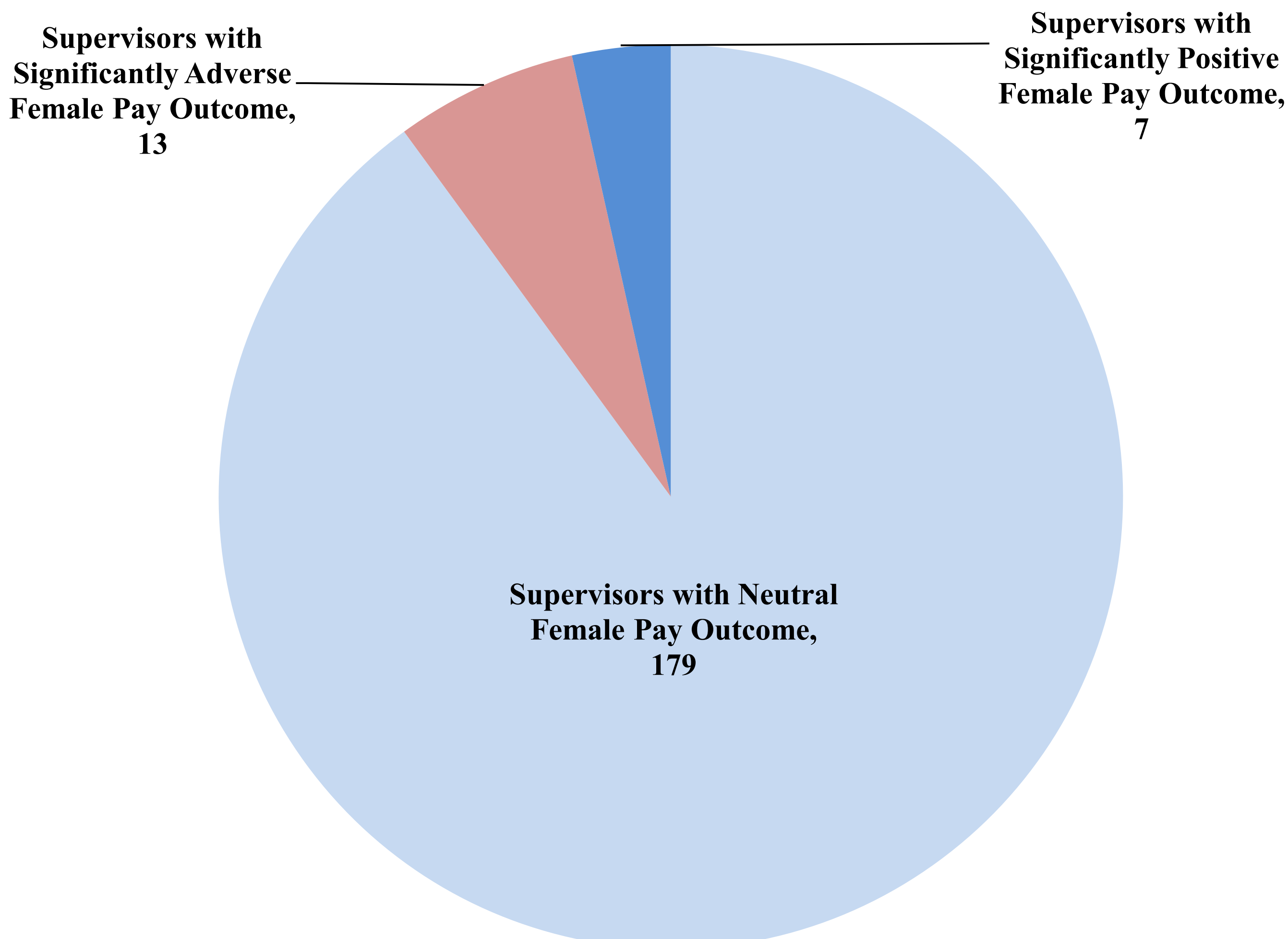
- Engineering & IT Operations, 2016 -



Note: Dr. Farber's pay Model 5 with Stock Level controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, Standard Title, and Stock Level. Analysis is limited to 46 out of 76 supervisors for whom the female coefficient and T-statistic can be calculated which accounts for 99% of women. 84% of women are under supervisors with neutral or significantly positive female pay outcome. 94% of women work in groups of 300 or more.

Level 3 Supervisors: Pay Outcomes for Women (Farber Model 5 with Stock Level)

- Engineering & IT Operations, 2016 -



Note: Dr. Farber's pay Model 5 with Stock Level controls for year, age, tenure at Microsoft, location, Pay Scale Type, performance, Discipline, Standard Title, and Stock Level. Analysis is limited to 199 out of 421 supervisors for whom the female coefficient and T-statistic can be calculated which accounts for 95% of women. 91% of women are under supervisors with neutral or significantly positive female pay outcome. 43% of women work in groups of 300 or more.

APPENDIX 2

APPENDIX 2:

FARBER ANALYSIS RESTRICTED TO CLASS PERIOD WITH NO OTHER CHANGES

Table 1

Gender Counts by Stock Level

2013 - 2016

Level	Employee Years	Count of Women	Percent Women	Count of Men	Percent Men	
59	[redacted]	2,337	20.0%	9,377	80.0%	In-Class Stock Levels
60	[redacted]	3,138	20.8%	11,945	79.2%	
61	[redacted]	4,660	20.7%	17,892	79.3%	
62	[redacted]	5,472	20.1%	21,763	79.9%	
63	[redacted]	4,263	16.4%	21,658	83.6%	
64	[redacted]	2,798	14.0%	17,197	86.0%	
65	[redacted]	1,289	11.4%	9,977	88.6%	
66	[redacted]	713	10.8%	5,901	89.2%	
67	[redacted]	259	6.7%	3,625	93.3%	
68	[redacted]	112	7.7%	1,349	92.3%	Out-Of-Class Stock Levels
69	[redacted]	44	6.1%	677	93.9%	
70	[redacted]	29	7.5%	358	92.5%	
80	[redacted]	10	7.0%	132	93.0%	
81	[redacted]	0	0.0%	22	100.0%	
82	[redacted]	0	0.0%	8	100.0%	
83	[redacted]	0	0.0%	4	100.0%	
0	[redacted]	147	23.3%	484	76.7%	
Overall	[redacted]	25,271	17.1%	122,369	82.9%	

Note: Stock level 0 is not directly comparable to other Stock Levels. Microsoft assigns employees to Stock Level 0 while they are awaiting assignment to a standard level.

This is all workers employed in Engineering or IT Professions in the listed Stock Levels whose annual salary is greater than $1. Annual Salary is coded as "1" during periods in which an employee in engaged in a Joint Venture with another company, and the other company, rather than Microsoft, processes that employee's payroll.

Table 2

Difference between Women's and Men's Total Compensation by Year

2013 - 2016

Year	Difference in Mean Total Compensation	T-Statistic on Difference in Total Compensation	Percent Difference in Mean Total Compensation	T-Statistic on Percent Difference in Mean Total Compensation	Employee Years
	[1]	[2]	[3]	[4]	[5]
2013	[redacted]	-20.48	-8.4%	-21.54	[redacted]
2014		-19.48	-8.1%	-20.93	
2015		-20.46	-8.3%	-21.05	
2016		-19.80	-8.3%	-20.19	
Overall		-23.67	-8.3%	-41.60	

Th is sample includes workers in Engineering or IT Operations Professions in Stock Levels 59-67 who are not employed in any professions other than Engineering or IT Operations at any point in the salary year, and who begin the year in Stock Levels 59-67. Additionally, this sample is limited to employee-years with non-missing values for tenure and age. I have also dropped employee-years in which annual salary is 1, or in which Career Stage is one of the following: ATR-C; ATR-D; ATR-E; IC-0; or MA.

Annual Salary is coded as "1" during periods in which an employee in engaged in a Joint Venture with another company, and the other company, rather than Microsoft, processes that employee's payroll.

Negative values in Columns [1] or [3] represent lower average compensation for Female Technical Employees.

Table 3

Difference between Women's and Men's Total Compensation by Year

2013 - 2016

	Log Point Difference	T-Statistic on Log Point Difference	P-Value	Percent Difference	Adjusted R^2	Employee Years
Model 1	-0.087	-23.461	< 0.005	-8.3%	0.009	[redacted]
Model 2	-0.073	-23.292	< 0.005	-7.0%	0.337	
Model 3	-0.072	-26.916	< 0.005	-6.9%	0 .503	
Model 4	-0.064	-24.610	< 0.005	-6.2%	0.538	
Model 5	-0.029	-19.715	< 0.005	-2.8%	0.770	

Model 1: Gender is the only explanatory variable
Model 2: Adds controls for "compensation year," employee age (and its square), employee tenure at Microsoft (and its square), state in which the employee works, city in which the employee works, and PayScaleType
Model 3: Adds controls for employees' performance ratings
Model 4: Adds controls for Discipline
Model 5: Adds controls for Standard Title

Table 4

Analysis of Gender Difference in Performance Metricx

2013 - 2016

	Coefficient on Female	T-Statistic	Employee Years
Contribution Ranking	-	-	[redacted]
Commitment Rating	-	-	
Performance Rating	-0.021	-1.62	
Reward Outcome	0.000	-0.01	

This table reports the results of order-probit analyses of employee performance ratings. Each row of this table concerns a distinct performance metric used by Microsoft. The only explanatory variable in each analysis is gender.

<u>Relevant Time Period for Each Metric:</u>

Contribution Ranking:	2011
Commitment Rating:	2011
Performance Rating:	2012-2014
Reward Outcome:	2015-2016

Farber Table 5

Stock Level A dvancement,

Men vs. Women, 2013-2015

Stock Level	Women	Men
59	50.6%	49.4%
60	45.3%	46.8%
61	34.9%	37.9%
62	25.0%	31.5%
63	22.7%	25.6%
64	18.2%	20.8%

A Stock Level advancement is defined as a change from a lower Stock Level into a higher Stock Level, comparing Stock Level on September 1 of year t with Stock Level on September 1 of year t-1.

Farber Table 6

Stock Level and Career Stage Advancement Differences for Men and Women

2013-2015

	Average Advancement Rate	Difference (Marginal Effect)	Z-statistic	Employee Years
	[1]	[2]	[3]	[4]
[A] Stock Level Advancement	0.327	-0.024	-7.653	[redacted]
[B] Career Stage Advancement prior to 2014	0.154	-0.030	-5.701	[redacted]
[C] Career Stage Advancement post 2014	0.288	-0.034	-3.069	[redacted]

Based on a probit analysis of an advancement measure on tenure, tenure squared, age, age squared, year, performance metrics, location, Discipline, and prior Stock Level in Row [A] or Career Stage in Rows [B] and [C].

Farber Table 7

Stock Level Advancement Shortfall

2013-2015

Stock Level	**Number of Observations (Employee-Years)** [1]	**Number of Woman-Years** [2]	**Number of Advancements, Women** [3]	**Advancement Rate, Women** [4]	**Expected Advancement Rate, Women** [5]	**Number of Expected Advancements, Women** [6]	**Shortfall of Advancements, Women** [7]	**T-Statistic** [8]
59	[redacted]	[redacted]	679	0.506	0.507	680	-1	-0.27
60			841	0.453	0.475	882	-41	-5.23
61			1,039	0.349	0.366	1,089	-50	-4.47
62			850	0.250	0.2 95	1,001	-151	-15.80
63			576	0.227	0.250	635	-59	-7.92
64			295	0.182	0.203	330	-35	-5.52

Total Shortfall, Stock Levels 59-64: 337

A Stock Level advancement is defined as a change from a lower Stock Level into a higher Stock Level, comparing Stock Level on September 1 of year t with Stock Level on September 1 of year t-1.

Based on a probit analysis of the Stock Level advancement indicator variable on tenure, tenure squared, age, age squared, year, performance metrics, location, Discipline, and prior Stock Level. This model is estimated for men only and the probability of Stock Level advancement is predicted for both men and women.

Reported Calculations and Results:

Column:	Reports:
[4] = [3] / [2]	Advancement Rate, Women
[5]: Result from Probit Model	Expected Advancement Rate, Women
[6] = [5] x [2]	Number of Expected Advancements, Women
[7] = [3] - [6]	Shortfall of Advancements, Women

Table 8

Damages Analysis

2013 - 2016

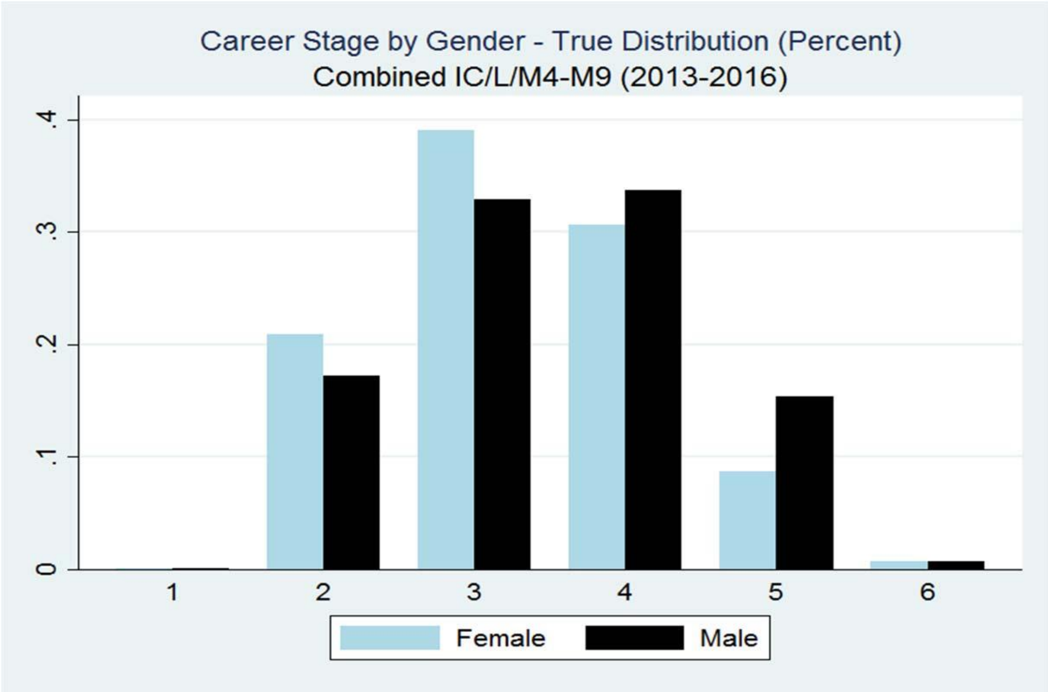
	Total Comp Gap (pct)	T-Statistic	Adjusted R^2	Employee Years	Damages
Model 1	-8.3%	-24.51	0.009	[redacted]	[redacted]
Model 2	-7.0%	-24.16	0.337		
Model 3	-6.9%	-27.91	0.503		
Model 4	-6.2%	-25.41	0.538		
Model 5	-2 .8%	-20.00	0.770		

Model 1: Gender is the only explanatory variable
Model 2: Adds controls for "compensation year", employee age (and its square), employee tenure at Microsoft (and its square), state in which the employee works, city in which the employee works, and PayScaleType
Model 3: Adds controls for employees' performance ratings
Model 4: Adds controls for Discipline
Model 5: Adds controls for Standard Title

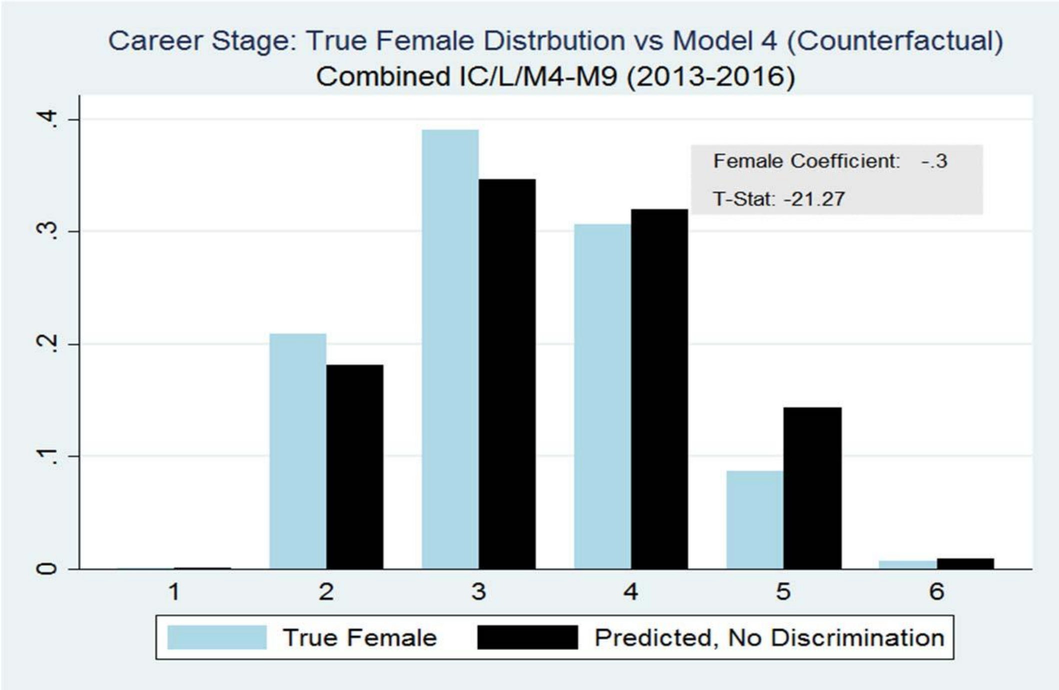
The total in-class compensation is: [redacted]

Note (Added): For all class members, the effective damages start date is September 16, 2012 (or hire date, if later). Dr. Farber's original analysis has May 14,2012 (or hire date, if later) as the effective damages start date for class members who terminated prior to July 18, 2013.

FIGURE 1

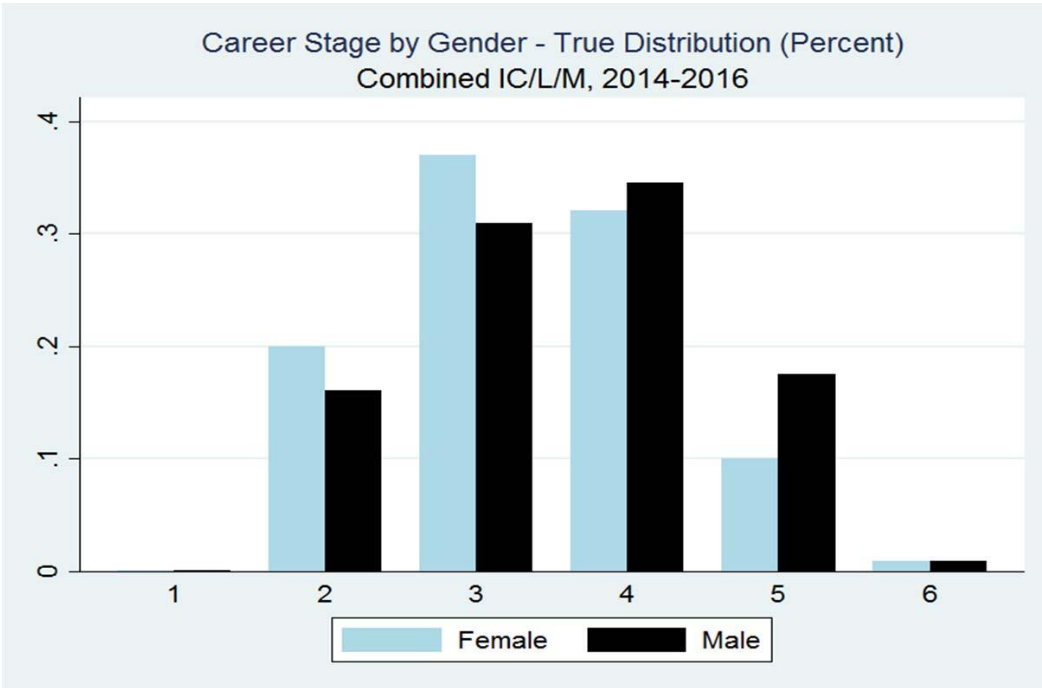


Note: The height of each bar represents the proportion of individuals in each career stage. I exclude M career stages 1-3 from this analysis.

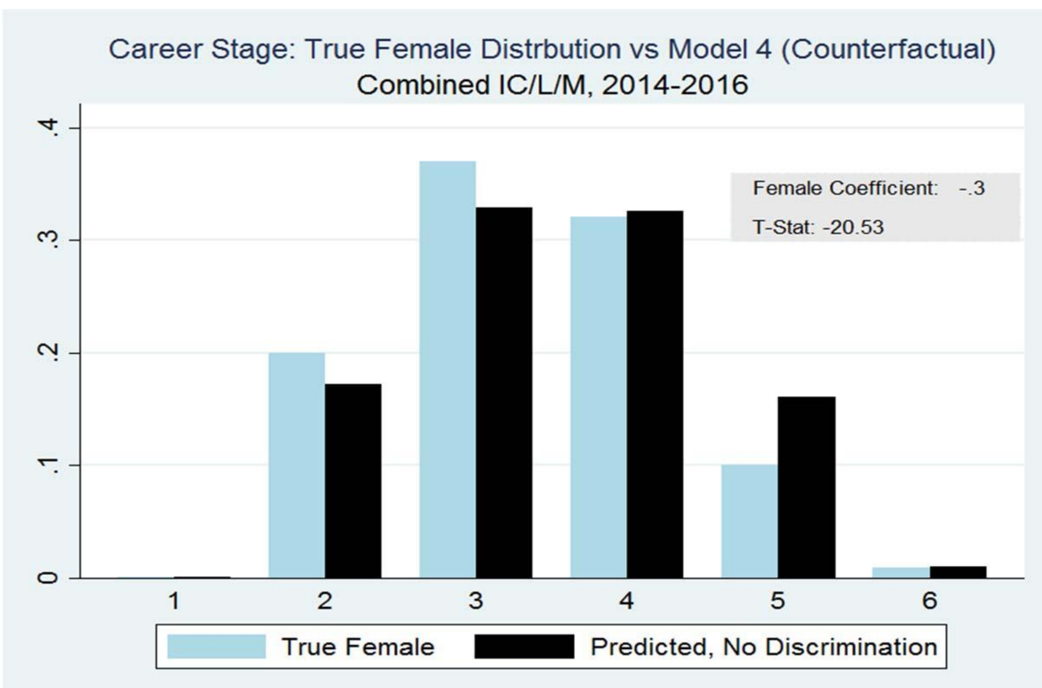


Note: The Predicted, No Discrimination distribution is calculated based on an ordered probit analysis that includes each employee's age, tenure, location, performance ratings, and Discipline, as well as the compensation year and an indicator for female. The coefficients of this analysis are used to predict the female distribution assuming each female was male (the female indicator set to zero) but otherwise had her observed characteristics. I exclude M career stages 1-3 from this analysis.

FIGURE 2

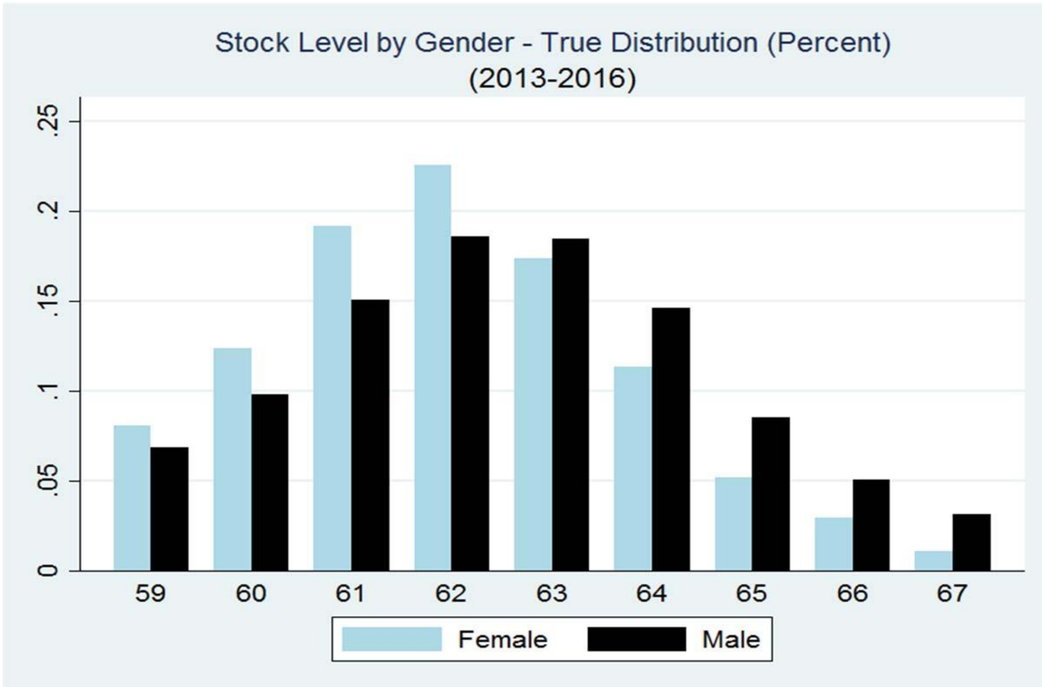


Note: The height of each bar represents the proportion of individuals in each Career Stage.

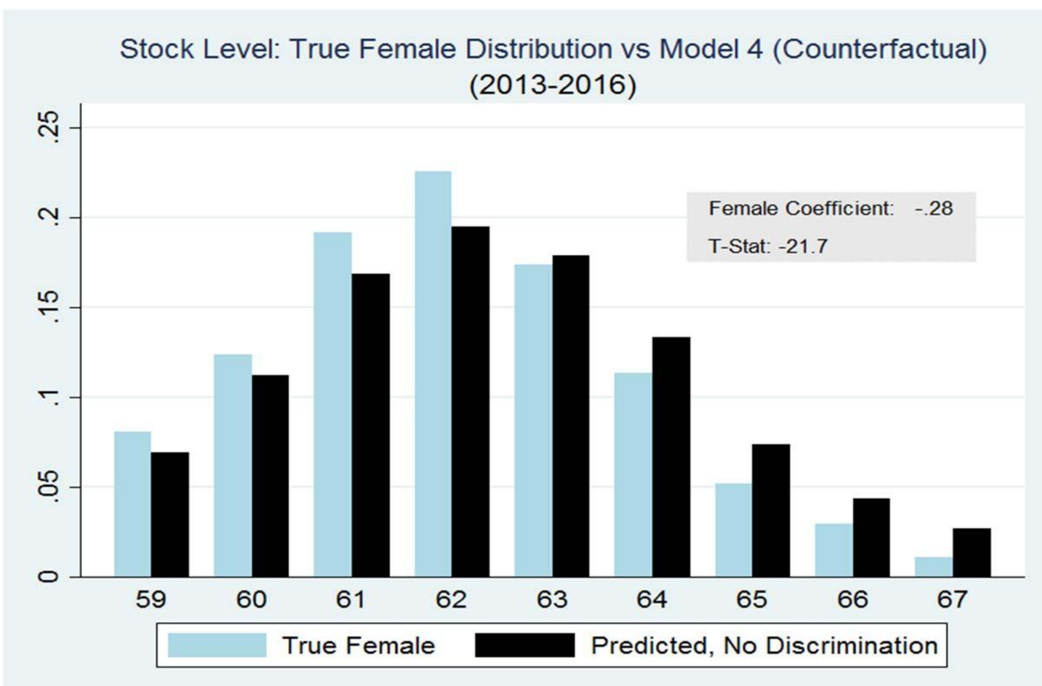


Note: The Predicted, No Discrimination distribution is calculated based on an ordered probit analysis that includes each employee's age, tenure, location, performance ratings, and Discipline, as well as the compensation year and an indicator for female. The coefficients of this analysis are used to predict the female distribution assuming each female was male (the female indicator set to zero) but otherwise had her observed characteristics.

FIGURE 3



Note: The height of each bar represents the proportion of individuals in each Stock Level.



Note: The Predicted, No Discrimination distribution is calculated based on an ordered probit analysis that includes each employee's age, tenure, location, performance ratings, and Discipline, as well as the compensation year and an indicator for female. The coefficients of this analysis are used to predict the female distribution assuming each female was male (the female indicator set to zero) but otherwise had her observed characteristics.

ATTACHMENT A

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ALI SAAD, Ph.D., MANAGING PARTNER

Dr. Saad is the Managing Partner of Resolution Economics LLC. He has a Ph.D. in Economics from the University of Chicago. Prior to Resolution Economics, Dr. Saad was a partner at Deloitte & Touche LLP and at Altschuler, Melvoin and Glasser LLP. Before that he was in the disputes consulting group at Price Waterhouse, first in New York, and then in Los Angeles. Prior to his consulting career, Dr. Saad served as an Assistant Professor of Economics at Baruch College of the City University of New York (CUNY).

Professional Experience

Dr. Saad's experience is extensive in the area of statistical and economic analysis of liability and damages related to employment litigation matters. His experience is extensive in the application of economics and statistical methods to class action employment discrimination matters. He is also experienced in designing, implementing, and analyzing surveys and observation studies as well as conducting empirical analyses related to exempt/non-exempt status, hours worked, uncompensated time, meal and rest breaks, rounding, and other wage and hour issues. He has also performed statistical and damages analyses for a broad range of commercial litigation matters including breach of contract, insurance coverage, environmental claims, patent infringement, antitrust and real estate financing. Dr. Saad has testified a number of times at deposition and trial. Dr. Saad also regularly consults to clients regarding business issues related to employment practices.

Employment Matters

Dr. Saad provides a variety of services related to employment litigation. His experience is extensive in conducting statistical and economic analysis related to issues of liability for employment discrimination matters. He also has designed and conducted many surveys and observational studies related to wage and hour issues. Dr. Saad has also performed analyses of economic damages in both class action and single plaintiff matters.

Statistical and Economic Analysis in Discrimination Matters

Assignments representative of Dr. Saad's experience in performing analyses in connection with employment discrimination matters include the following:

- Consulting and expert witness services in national class action race discrimination matter involving issues of pay, promotion, work assignment, and a variety of other challenged employment practices. Services included creating databases from diverse and voluminous source materials, and conducting extensive statistical analyses.

- Consulting and expert witness services in national class action gender discrimination matter involving issues of job assignment and promotion. Services included creating databases from diverse and voluminous source materials, and conducting extensive statistical analyses.

- Consulting and expert witness services in a class action case alleging that contracts were misleading. Services included processing and analyzing large quantities of data, and performing statistical analysis of the criteria determining class membership.

- Consulting and expert witness services in connection with a major class action alleging gender discrimination in pay and promotion at a large high-tech employer. Services included creating analytical databases, and developing economic and statistical arguments concerning the relationship between productivity-related variables, pay/promotion, and gender.

- Consulting and expert witness services in an antitrust and discrimination matter in which a group of businesses alleged violations of antitrust and discrimination laws by another group of businesses. Services included data construction, and statistical analysis related to issues of liability.

- Consulting and expert witness services on behalf of plaintiffs' counsel in a series of cases alleging race discrimination in hiring. Services included creating analytical databases, studying the relationship between race and hiring, and examining the features of the external labor market.

- Consulting and expert witness services in connection with a class action claim of discrimination based on age in connection with a series of layoffs resulting from the combination of two large retail chains. Services included creating analytical databases, studying the relationship between layoff and age, and examining the relationship between age and workforce composition over.

- Consulting and expert witness services in connection with EEOC allegations of race discrimination in recruiting, hiring, and initial placement at a large service providing company. Services included developing databases from diverse paper and electronic sources, and providing statistical arguments concerning the relationship between race and various other factors.

- Consulting and expert witness services to defendant's counsel in connection with a major class action alleging gender discrimination in multiple employment practices at a national retail chain. Services included developing a database from voluminous paper documents, and conducting analysis related to hiring, initial placement, and initial pay.

- Consulting and expert witness services to defendant's counsel in connection with an EEOC investigation of racial discrimination in hiring by a major service providing organization. Services included developing a database, and conducting statistical analysis related to hiring.

- Consulting services to defendant's counsel in connection with a U.S. Department of Labor OFCCP investigation of pay equity at a high-tech company. Services included design and oversight of a statistical analysis of pay equity, assessment of the OFCCP methodology, and participation in conciliation discussions between the company and the OFCCP.

- Consulting and expert witness services to defendant's counsel in connection with an allegation of age discrimination in terminations resulting from a series of mass layoffs. Services provided included developing statistical arguments concerning the relationship between age and termination.

- Consulting services to defendant’s counsel in connection with a Department of Justice investigation regarding allegations of racial profiling by a large city police department. Analyzed departmental data related to over 130,000 traffic stops, pedestrian stops, and other types of police contacts that occurred in four selected weeks in 1997 and four selected weeks in 1999. Cross-referenced traffic stops data with other information sources including human resources data, precinct level paper records, and the officer discipline system to test various hypotheses.

- Consulting services and expert testimony to defendant’s counsel in connection with a multi-plaintiff matter alleging race and gender discrimination in promotion and placement into coveted positions by a large city police department. Performed statistical analysis of promotion and placement into coveted positions. Quantified economic damages for several plaintiffs under failure to promote and wrongful termination theories.

- Consulting services in a case against a city government alleging discrimination in recruiting and hiring of police and firefighters. Services included using Census and other large-scale data sources to assess labor market characteristics by detailed geographic location, and conducting extensive analysis of the impact of employment tests on hiring.

- Consulting and expert witness services to defendant’s counsel in a matter where plaintiff alleged that defendant’s hiring practices discriminated against women. Services included converting diverse paper source materials into a usable database, and developing statistical evidence concerning plaintiff’s allegation.

- Consulting services in several class action recruiting and hiring matters. Services included use of detailed census and other data to estimate labor market availabilities by geographic location, and analyzing employment practices in light of these availability findings.

- Consulting services to a major bank involved in an analysis of its fair lending practices. Services included using bank data on applicants for mortgages and other loans, and adding various demographic and geographic information to assess if the bank made loans on the basis of race, or controlling for other, observable factors could explain patterns in loan making.

- Consulting services on behalf of defendant’s counsel in a major class action matter involving allegations of gender discrimination in promotion. Services included building analytical database from many sources, using the database to conduct extensive statistical analysis of plaintiffs’ allegations, and estimating damages resulting from non-promotion for approximately 3,000 women occupying different jobs over a ten-year period.

- Consulting and expert witness services on behalf of defendant’s counsel in two related cases alleging age discrimination in termination. Prior to plaintiffs’ vesting for certain long term benefits. Services included using defendant’s human resource data to test plaintiffs’ specific allegations, developing statistical arguments concerning the relationship between age and termination, and performing analyses of plaintiff’s damages in each case.

- Consulting services on behalf of plaintiff’s counsel in distribution of award in an age discrimination matter with 75 plaintiffs. Services included developing a method to efficiently compute damages for all plaintiffs, and working with counsel, an arbitrator, and a committee of plaintiffs to explain the process to the plaintiff group.

Wage and Hour Matters

Assignments representative of Dr. Saad's experience in wage and hours matters include:

- Consulting and expert witness services to defense counsel in a national class-action wage and hour matter alleging that several thousand loan originators at a large financial institution were misclassified under FLSA. Conducted statistical analyses of hours worked records, compensation data, plaintiffs' declarations, and other data to determine if select groups of plaintiffs would be representative of the class.

- Consulting and expert witness services to defense counsel in a wage and hour matter alleging that several thousand General Managers and Assistant Managers at a large office supply retailer were misclassified as exempt employees. Services included designing and conducting a survey to examine whether class members were appropriately classified, analyzing the company's labor model and human resources data, and conducting statistical analyses related to a variety of class certification issues.

- Consulting and expert witness services to defense counsel in a wage and hour matter alleging that several thousand Assistant Managers at a large general merchandise retailer were misclassified as exempt employees. Services included designing and conducting both a survey and an observational study, to examine whether or not class members were appropriately classified. Services also included conducting extensive statistical analyses of the data collected by the survey and the observational study, and preparing materials for use in class certification proceedings.

- Consulting services to defense counsel in a class action matter alleging failure to pay overtime wages to independent sales and service representatives for a large national tool franchiser. Services included designing and implementing an hours survey to determine whether the additional hours worked claimed by some plaintiffs was representative of the additional hours worked by the class as a whole. Determined that the problem were isolated to certain geographic areas rather than nationwide.

- Consulting and expert witness services to defense counsel in a wage and hour matter alleging that several hundred store managers and assistant store managers at a chain of retail discount stores were misclassified. Services included creating and implementing a survey to examine whether class members were classified appropriately and conducting statistical analyses related to commonality of class-members and other class certification issues.

- Consulting services to defense counsel in a multi-plaintiff wage and hour matter alleging that the defendant employer failed to compensate security guards for uniform changing time and other claims of off-the-clock work. Services included designing and conducting an observation study to measure time associated with various activities.

- Consulting services to defense counsel in wage and hour matter alleging that store managers at a chain of convenience store/ gas station operations were misclassified as exempt workers. Services included designing and conducting a random sampling scheme and observational study to evaluate the amount of time that class members spent on exempt and non-exempt duties.

- Consulting services to defense counsel in a class-action wage and hour matter alleging uncompensated meal periods and breaks, unpaid overtime wages, and minimum wage violations at a field maintenance company.

Services included creating a database of hours worked from paper and electronic records, and then providing damages estimates based on a variety of assumptions and legal theories.

- Consulting services to defense counsel in a class action matter alleging a variety of wage and hour violations for hourly workers at a chain of warehouse stores. Services included analyzing data to test allegations of improper time adjustments, missed meal and rest periods, uncompensated split shifts, reporting time violations, overtime and regular rate issues, and off-the-clock work.

Employment Damages

Assignments representative of Dr. Saad's experience estimating economic damages include the following:

- Consulting services to plaintiff's counsel in a case involving a breach of employment contract allegation by a high-level executive in the emerging communications industry. Services included damages analysis based on valuation of stock options and estimation of future earnings.

- Consulting services to defendant's counsel in a case involving a wrongful termination allegation by a high-level executive in the telecommunication industry. Services included damages analysis based on valuation of stock options using the Black-Scholes Option Pricing Framework and a Monte Carlo Simulation Model.

- Consulting and expert witness services on behalf of defendant's counsel in a matter brought by a former executive who alleged wrongful termination and age discrimination against a major defense contractor following a reduction in force. Critiqued work product of the opposing expert, evaluated mitigation issues, calculated loss of earnings damages and valued losses related to stock options.

- Consulting and expert witness services on behalf of defendant's counsel in a medical malpractice action where the underlying damages issue was valuing an income stream from a closely held cash business. Performed accounting of plaintiff's financial records to determine the existence and the extent of fraud. Created financial models to calculate damages under a variety of scenarios.

- Consulting and expert witness services to defendant's counsel in a wrongful termination matter brought by senior executive of a high-tech company who alleged age discrimination. Performed analysis of mitigation factors, calculated loss of earnings, and valued future stock options.

Commercial Litigation

Dr. Saad has assisted clients in a variety of commercial litigation matters, including patent infringement, insurance coverage, antitrust, breach of contract, and real estate financing. Assignments representative of Dr. Saad's experience in these areas include the following:

- Consulting and expert witness services in a series of cases involving the real property title insurance industry. Services included performing extensive statistical analyses in connection with both liability and damages issues.

- Consulting and expert witness services in a case alleging breach of loan commitment to a commercial real estate concern. Services included constructing financial models, developing economic arguments relating to fixed versus variable rate loans, and assisting counsel in deposing the opposing expert.

- Consulting and expert witness services in a case involving a breach of contract allegation in the computer hardware industry. Services consisted of performing a damages calculation, and rebutting the opposing expert's analysis.

- Consulting and expert witness services in a case alleging that one entity caused another entity's property to be misused. Services included database creation, and statistical analysis related to issues of causation. Results indicated that there was a statistically significant relationship between defendant's actions and plaintiff's economic condition.

- Consulting services on behalf of defendant's counsel in a breach of contract matter in the context of natural resource raw materials shipping. Services included developing economic arguments regarding the but-for pricing of both the shipping service as well as the material being shipped.

- Consulting and expert witness services on behalf of defendant's counsel in a major insurance coverage case, in which the underlying claims resulted from tens of thousands of asbestos claims. Services included developing strategy for dealing with large amounts of paper information, creating a database for analysis, and performing a variety of statistical analyses.

- Consulting services on behalf of plaintiff's counsel in an antitrust matter in the consumer electronics product market. The antitrust practice alleged was predatory pricing. Services included preparing a damage analysis.

- Consulting services on behalf of defendant's counsel in a patent infringement matter in the computer hardware industry. Services included researching transfer pricing issues and analyzing complex company P&L data in preparation for damages calculation.

- Consulting services on behalf of defendant's counsel in a real estate financing dispute. Dispute revolved around the financing of a major New York office property. Services included analysis of interest rates and their relationship to potential damages at various points in time, as well as the construction of a financial model of the property with the but-for financing in place.

- Consulting services on behalf of plaintiff's counsel in an antitrust matter involving allegations of non-competitive practices and predatory pricing in the home cable television market. Services included an analysis of "raising rivals costs", as well as a statistical analysis of pricing of complex products over time.

Summary of Employment Experience

Resolution Economics LLC:
Managing Partner, October 1998 to date.

University of Southern California
Adjunct Associate Professor in the Department of Economics**,** January 1999 to September 2001.

Deloitte & Touche, LLP:
Partner, Dispute Consulting Services, (Los Angeles), 1998.

Altschuler, Melvoin and Glasser LLP:
Partner, Economics and Litigation Services, (Los Angeles), 1995 to 1998.

Price Waterhouse LLP:
Senior Manager, Manager, Litigation and Corporate Recovery Services Group, (New York and Los Angeles), January 1989 – November 1989, June 1990 to 1995.

Olympia & York Companies (USA):
Assistant VP and Senior Economist, (New York), November 1989 - June 1990.

Baruch College, City University of New York (CUNY):

Instructor and Assistant Professor of Economics, Department of Economics and Finance, 1982-1988; Center for the Study of Business and Government, Research Associate, 1983-1986; U.S. Small Business and Veterans Administrations, Consultant, 1985-1986.

Education

Ph.D., Economics, The University of Chicago.

B.A., History, Economics, The University of Pennsylvania

Publications

Financial Success and Business Ownership among Vietnam and other Veterans (with S. Lustgarten) SBA - 7210 - VA - 83, 1986.

"Schooling and Occupational Choice in 19th Century Urban America", Journal of Economic History, vol. 49, no. 2, June 1989.

"Employment Discrimination Litigation", chapter in Litigation Services Handbook, ed. by Roman Weil, et al., 1995, 2001, 2006, 2012, 2017.

“Employment Discrimination”, chapter in Litigation Support Report Writing, ed. by Jack P. Friedman, et al, 2003.

Paul Grossman, Paul Cane, and Ali Saad, "Lies, Damned Lies, and Statistics: How the Peter Principle Warps Statistical Analysis of Age Discrimination Claims", The Labor Lawyer, vol. 22, no. 3, Winter/Spring 2007, pp. 251-268.

Saad, Ali, "Beyond the Peter Principle – How Unobserved Heterogeneity in Employee Populations Affects Statistical Analysis in Age Discrimination Cases: Application to a Termination/RIF Case", AELC Conference Volume, 2007.

Saad, Ali, "Filling the Data Vacuum in Wage and Hour Litigation: The Example of Misclassification Cases, Emphasis on Class Certification", SIOP Annual Conference Proceedings, 2009.

Saad, Ali, "Wage and Hour Cases - Filling the Data Vacuum: Misclassification Cases and Other Observational Studies", SIOP Annual Conference Proceedings, 2012.

Presentations

Dr. Saad has delivered many presentations at professional conferences, to law firms and to industry groups.

Academic Honors

Finalist, Allan Nevins National Doctoral Dissertation Award
NIMH Doctoral Fellowship, The University of Chicago
Magna Cum Laude, The University of Pennsylvania
Honors in History, Economics, The University of Pennsylvania
Omicron Delta Epsilon, Honor Society in Economics

Professional Affiliations

American Economic Association
American Statistical Association
American Bar Association (associate membership)

Ali I. Saad, Ph.D.
Attachment to Resume

Testimony, Expert Reports, and Declarations:

In the matter of Woods, et al., v. JFK Memorial Hospital, Inc., Case No. INC 1205209, (Superior Court of California, County of Riverside), in connection with wage and hour claims. Report filed October 13, 2017. Deposition November 29, 2017.

In the matter of Bridewell-Sledge, et al., v. Blue Cross of California, et al., Case No. BC 477 451 c/w BC 481 586, (Superior Court of California, County of Los Angeles), in connection with employment discrimination claims. Report filed September 7, 2017. Deposition October 30, 2017.

In the matter of Stewart, et al, v. Hat World, et al., Case No. CIV 533617, (Superior Court of California, County of San Mateo), in connection with wage and hour claims. Report filed September 7, 2017.

In the matter of Truitt, et al., v. Atlanta Independent School System, Case No. 1:15-cv-4295-SCJ-WEJ, (United States District Court, Northern District of Georgia, Atlanta Division), in connection with allegations of employment discrimination. Report filed August 31, 2017. Deposition September 20, 2017.

In the matter of Williams, et al., v. TGI Fridays, Inc. Case No. 15-cv-0426, (United States District Court, Northern District of Illinois), in connection with allegations of wage and hour violations. Report filed August 4, 2017, deposition August 25, 2017.

In the matter of Whitaker, et al., v. U.S. Renal Care, Inc., et al, Case No. 1:17-cv-02661-GJSx), (United States District Court, Central District of California), in connection with allegations of wage and hour violations. Report filed July 17, 2017.

In the matter of Victor Cejka, et al., v. Vectrus Systems Corporation, et al. Case No. 15-cv-02418-MEH, (United States District Court, District of Colorado), in connection with alleged employment damages. Report filed July 17, 2017, Rebuttal report filed August 14, 2017.

In the matter of EEOC, v. GMRI, Inc. Case No. 15-cv-20561-JAL, (United States District Court, Southern District of Florida, Miami Division), in connection with allegations of employment discrimination. Report filed April 21, 2017, deposition June 8, 2017.

In the matter of Coordinated Proceedings, Special Title, Staples Wage and Hour Cases (Included Actions: Lawson, et al. v. Staples Contract and Commercial, Inc., Los Angeles County Superior Court, Case No. BC542237, and Rosales v. Staples Contract and Commercial, Inc., San Bernardino Superior Court, Case No. CIVDS 1505146), in connection with wage and hour allegations. Report filed May 16, 2017.

In the matter of Curtis Patton, et al. v. Dollar Tree Stores, et al. Case No. 2:15-cv-03813 MWF-PJW, (United States District Court, Central District of California), in connection with wage and hour allegations. Rebuttal Report filed May 15, 2017.

In the matter of Bowerman, et al., v. FAS, Civil Action No. 13-00057-WHO, (United States District Court, Northern District of California), in connection with wage and hour allegations. Rebuttal Report filed April 6, 2017, deposition April 11, 2017.

In the matter of Romero, et al., v. Allstate Insurance Company, et al., Consolidated Cases, Civil Action No. 01-3894-MAK, (United States District Court, Eastern District of Pennsylvania), in connection with employment discrimination allegations. Rebuttal Report filed March 20, 2017, deposition March 29, 2017.

In the matter of Wall v. HP Inc., et al. Case No. 30-2012-00537897-CU-BT-CXC, (Superior Court of the State of California, County of Orange), in connection with wage and hour allegations. Declaration filed March 14, 2017.

In the matter of Controulis, et al., v. Anheuser-Busch, LLC, et al., Case No. BC-518518, (Superior Court of the State of California, County of Los Angeles), in connection with wage and hour allegations. Report filed December 12, 2016.

In the matter of Urbano, et al., v. SMG Holdings, et al., Case No.: 5:15-cv-00603-MMM (MRW), (United States District Court for the Central District of California), in connection with wage and hour allegations. Report filed October 14, 2016, deposition October 26, 2016.

In the matter of Williams, et al., v. Baker Hughes Oilfield Operations, Case No.: 1:15-cv-00049-RRE-ARS, (United States District Court for District of North Dakota), in connection with wage and hour allegations. Reports filed June 24, 2016, January 12, 2017.

In the matter of In re: AutoZone, Inc., Wage and Hour Employment Practices Litigation, Case No.: 3:10-cv-02159-CRB (JSC), (United States District Court for the Northern District of California), in connection with wage and hour allegations. Report filed April 29, 2016, deposition May 27, 2016.

In the matter of EEOC v. Texas Roadhouse, Inc., et al. Case No.:1:11-cv-11732 (United States District Court for the District of Massachusetts), in connection with allegations of age discrimination. Reports filed April 22, 2016 and July 20, 2016. Deposition June 17, 2016; trial testimony January 26, 2017.

In the matter of Luanna Scott, et al., v. Family Dollar Stores, Inc., Case No.:3:08-cv-540 (United States District Court for the Western District of North Carolina), in connection with allegations of gender discrimination. Reports filed January 28, 2016, May 31, 2016. Deposition February 10, 2016.

In the matter of Brown, et al., v. In-N-Out Burger, Inc., Case No.:RG12646351 (Superior Court for the State of California, County of Alameda), in connection with allegations of age discrimination. Report filed December 23, 2015.

In the matter of Valerie Horvath v. Western Refining Wholesale, Inc., Case no. Case No.:CIV-ds1311846 (Superior Court for the State of California, County of San Bernardino), in connection with allegations of age discrimination. Report filed November 19, 2015. Deposition January 14, 2016.

In the matter of Cortina, et al., v. North American Title Company, Case no. 07 CE CG 01169 JH, (Superior Court of the State of California, County of Fresno), in connection with class action employment matter. Reports filed May 11, 2012, June 25, 2012, and August 13, 19, 21, and 26, 2015. Deposition September 8 and 9, 2015. Trial testimony December 3 and December 10, 2015.

In the matter of Curley, et al., v. Savemart, et al. Case no RG13685740, (Superior Court of California, County of Alameda), in connection with class action wage and hour matter. Report filed September 2, 2015. Deposition December 18, 2015 and January 20, 2016.

In the matter of Gamble, et al., v. Boyd Gaming Corporation, et al., Case no. 2:13-cv-01009-JCM-PAL, (US District Court, District of Nevada), in connection with class action wage and hours claim. Report filed January 26, 2015.

In the matter of Chea, et al., v. Best Buy Stores. Case no 4:14-cv-0020-PJH, (United States District Court, Northern District of California, Oakland Division), in connection with class action wage and hour matter. Report filed March 13, 2015.

In the matter of Ruffin, et al., v. Avis Budget Car Rental LLC, et al., Case no. 11-01069-SDW-MCA, (US District Court, District of New Jersey), in connection with class action wage and hours claim. Report filed December 19, 2014.

In the matter of Campese v. County of Los Angeles, et al., Case no. BC-498147, (Superior Court of the State of California, County of Los Angeles), regarding analysis of data in connection with claim of age discrimination. Deposition October 4, 2014, Trial testimony, December 12, 2014.

In the matter of Ellis, et al., v. Costco Wholesale, Inc., Case no. C-04-3341-EMC, (United States District Court for the Northern District of California), regarding statistical analysis in employment discrimination class action. Reports filed June 22, 2006, August 18, 2006, October 16, 2014, November 14, 2014, and December 12, 2014. Deposition June 29, 2006.

In the matter of Melera, et al. v. Securitas Security Services, USA, Case no. BC-394708, (Superior Court of the State of California, County of Los Angeles), regarding analysis of data in connection with wage and hours claim. Deposition October 21, 2014.

In the matter of Becerra, et al., v. The McClatchy, et al., Case no. 08-CECG-04411-KCK, (Superior Court for the State of California, County of Fresno), regarding the use of statistical analysis in an employment matter. Deposition October 21, 2014.

In the matter of Salgado, et al., v. The Daily Breeze, et al., Case no. BC458074, (Superior Court for the State of California, County of Los Angeles), regarding the use of statistical analysis in a wage and hours matter. Report filed September 24, 2014.

In the matter of Hurt, et al., v. Commerce Energy, Inc, et al., Case no. 1:12-CV-00758, (United States District Court for the Northern District of Ohio), regarding analysis of data in connection with federal and state class action wage and hour claims. Reports filed May 29 and June 17, 2014. Deposition June 24, 2014

In the matter of Alequin, et al., v. Darden Restuarants, Inc., et al., Case no. 12-61742-CIV-ROSENBAUM/SELTZER, (United States District Court for the Southern District of Florida), regarding statistical sampling. Declaration filed December 16, 2013. Regarding analysis of employee work experiences, Report filed April 16, 2014, Deposition May 12, 2014.

In the matter of Kaanaana, et al., v. Barrett Business Services, et al., Case no. BC497090, (Superior Court for the State of California, County of Los Angeles CCW), regarding the use of statistical analysis in an employment matter. Report filed January 24, 2014. Deposition January 11, 2016

In the matter of Sawin, et al., v. The McClatchy, et al., Case no. 34-2009-00033950-CU-OE-GDS, (Superior Court for the State of California, County of Sacramento), regarding the use of statistical analysis in an employment matter. Report filed November 1, 2013, deposition December 5, 2013.
In the matter of Andrews, et al., v. Lawrence Livermore National Security, LLC, Case no. RG09453596, (Superior Court for the State of California, County of Alameda), regarding statistical analysis in an employment discrimination matter), Deposition October 16, 2013, Trial testimony December 12, 2013.

In the matter of Rahmon Momoh v. CPUC, Case no. CGC-12-519287, (Superior Court for the State of California, County of San Francisco), regarding the use of statistical analysis in an employment discrimination matter. Report filed June 28, 2013.

In the matter of Robert Zator and Carlos Garcia, et al., v. Sprint/United Management Case no. 37-2009-00098691-CU-OE-CTL, (Superior Court for the State of California, County of San Diego), regarding the use of statistical analysis in a PAGA claim related to expense reimbursements. Report filed June 26, 2013.

In the matter of Benjamin Paparella, et al. v. JPMorgan Chase Bank, Case no. 30-2010-00370146-CU-OE-CXC, (Superior Court of the State of California, County of Orange), in connection with plaintiffs' proposed trial management statistical sampling plan. Report filed July 3, 2013, Deposition August 8, 2013.

In the matter of Romo, et al. v. GMRI, Inc, dba Olive Garden, et al., Case no. EDCV 12-00715 JLQ-SPX, (United States District Court, Central District of California), in connection with statistical analysis in a wage and hours claim. Report filed July 11, 2013, Deposition August 21, 2013.

ATTACHMENT B

Attachment B – List of Documents

I. Microsoft Data and Documents

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MSFT_MOUSSOURIS_00121407 (Current_All.xlsx)
MSFT_MOUSSOURIS_00121408 (JobHistory_1st15000.xlsx)
MSFT_MOUSSOURIS_00121409 (JobHistory_2nd14000.xlsx)
MSFT_MOUSSOURIS_00121410 (JobHistory_3rd15500.xlsx)
MSFT_MOUSSOURIS_00121411 (JobHistory_4th21537.xlsx)
MSFT_MOUSSOURIS_00121412 (OnHireSalary_All.xlsx)
MSFT_MOUSSOURIS_00121413 (PeopleReview_1st35000.xlsx)
MSFT_MOUSSOURIS_00121414 (PeopleReview_2nd31037.xlsx)
MSFT_MOUSSOURIS_00121415 (Staffing_1st37500.xlsx)
MSFT_MOUSSOURIS_00121416 (Staffing_2nd28537.xlsx)
MSFT_MOUSSOURIS_00308280
MSFT_MOUSSOURIS_00308288 (MRT FY 2015_v2.txt)
MSFT_MOUSSOURIS_00308289 (MRT FY 2016_v2.txt)
MSFT_MOUSSOURIS_00642050
MSFT_MOUSSOURIS_00646650
MSFT_MOUSSOURIS_00646650 (Compensation_Supp.xlsx)
MSFT_MOUSSOURIS_00646651 (Current_Supp.xlsx)
MSFT_MOUSSOURIS_00646652 (JobHistory_Supp.xlsx)
MSFT_MOUSSOURIS_00646653 (OnHireSalary_Supp.xlsx)
MSFT_MOUSSOURIS_00646654 (PeopleReview_Supp.xlsx)
MSFT_MOUSSOURIS_00646655 (Staffing_Supp.xlsx)
MSFT_MOUSSOURIS_00646656 (MRT FY 2014 – Additional Personnel Numbers.txt)
MSFT_MOUSSOURIS_00652803 (MRT FY 2014 – Personnel# - 7255 – Special Case.txt)
MSFT_MOUSSOURIS_00652833 (MRT FY 2015 – Additional Personnel Numbers.txt)
MSFT_MOUSSOURIS_00654726 (MRT FY 2016 – Additional Personnel Numbers.txt)
MSFT_MOUSSOURIS_00656115 (MRT Promotions 30Apr2016 – Additional Personnel Numbers.txt)
MSFT_MOUSSOURIS_00656602 (NRP Promotions – Additional Personnel Numbers.txt)
MSFT_MOUSSOURIS_00672297 (Performance Management – Additional Personnel Numbers.txt)

MSFT_MOUSSOURIS_00684212 (Revenue Bonus ALL.xlsx)
MSFT_MOUSSOURIS_00688508
MSFT_MOUSSOURIS_00741588
MSFT_MOUSSOURIS_00752987 (MRT FY 2014.txt)
MSFT_MOUSSOURIS_00752988 (MRT FY 2015.txt)
MSFT_MOUSSOURIS_00752989 (MRT FY 2016.txt)
MSFT_MOUSSOURIS_00752990 (MRT Promo.txt)
MSFT_MOUSSOURIS_00752991 (Performance Management.txt)
MSFT_MOUSSOURIS_00807111
MSFT_MOUSSOURIS_00807112
MSFT_MOUSSOURIS_00807113
MSFT_MOUSSOURIS_00807114
MSFT_MOUSSOURIS_00807115
MSFT_MOUSSOURIS_00807207 (CTRL_00000001 Highly Confidential – AEO.dat)
MSFT_MOUSSOURIS_00808607 (MRT FY 2016.txt)
MSFT_MOUSSOURIS_00821129 (MIC2_Payments.xlsx)
MSFT_MOUSSOURIS_00821130 (xCAT_Payment_Results.xlsx)
MSFT_MOUSSOURIS_00860376
MSFT_MOUSSOURIS_00860379
MSFT_MOUSSOURIS_00860387
MSFT_MOUSSOURIS_00860390
MSFT_MOUSSOURIS_00880295 (CELA_Moussouris_Population_ASG AEO_Highly Confidential.xlsx)
MSFT_MOUSSOURIS_00880296 (CELA_Moussouris_Population_C+E AEO_Highly Confidential.xlsx)
MSFT_MOUSSOURIS_00880297 (CELA_Moussouris_Population_COO AEO_Highly Confidential.xlsx)
MSFT_MOUSSOURIS_00880298 (CELA_Moussouris_Population_S&M AEO_Highly Confidential.xlsx)
MSFT_MOUSSOURIS_00880299 (CELA_Moussouris_Population_T&R AEO_Highly Confidential.xlsx)
MSFT_MOUSSOURIS_00880300 (CELA_Moussouris_Population_WDG AEO_Highly Confidential.xlsx)
MSFT_MOUSSOURIS_00883720
MSFT_MOUSSOURIS_00883721
MSFT_MOUSSOURIS_00883722

<u>Data files sent to Plaintiffs' counsel through Kiteworks by C. Heckman on December 16, 2016 (in MICRO-01634_RequestedFields_20161216 (2).zip):</u>

MFT FY15 - vwRewardsDailyBudgetData Highly Confidential_AEO

MFT FY15 - vwRewardsDailyData Highly Confidential_AEO
MFT FY16 - vwRewardsDailyBudgetData Highly Confidential_AEO
MFT FY16 - vwRewardsDailyData Highly Confidential_AEO
IRRStockFeed Highly Confidential_AEO
vwSalaryPlan Highly Confidential_AEO

Data files sent to Plaintiffs' counsel through Kiteworks by C. Heckman on February 3, 2017 (in 2.3.2017 Reward Database Export.zip):

2014 Highly Confidential AEO
2015 - Standalone - Extracts Highly Confidential AEO
2015 Highly Confidential AEO
2016 - Standalone - Extracts Highly Confidential AEO
2016 Highly Confidential AEO
NRP - InBudgetCalc - Standalone - Extracts Highly Confidential AEO
NRP - Promo Budget Company Fields - Standalone - Extracts Highly Confidential AEO
NRP - Promo Budget Employee Fields - Standalone - Extracts Highly Confidential AEO
Performance - StandAlone Extracts Highly Confidential AEO
Performance Highly Confidential AEO

II. Correspondence

Apr 15, 2016 Email from Orrick to Plaintiffs (Subject: Moussouris meet and confer)
May 24, 2016 Ltr from Plaintiffs to Orrick re MS People fields
May 31, 2016 Ltr from Plaintiffs to Orrick re Reward databases and MS People
June 3, 2016 Email from Orrick to Ptfs (Subject: RE Moussouris v. Microsoft – Letter)
June 28, 2016 Ltr from Orrick to Plaintiffs re MS People
July 12, 2016 Ltr from Orrick to Plaintiffs re Structured Data Productions
July 22, 2016 Ltr from Orrick to Plaintiffs re MS People
July 25, 2016 Ltr from Plaintiffs to Orrick re Scope of Structured Data production
July 28, 2016 Ltr from Plaintiffs to Orrick (OGDMS_898853_1.pdf)
Aug 2, 2016 Ltr from Orrick to Plaintiffs re Structured Data
Aug 8, 2016 Email from Orrick to Plaintiffs re Reward Database productions
Aug 11, 2016 Ltr from Plaintiffs to Orrick re Reward fields
Aug 16, 2016 Ltr from Plaintiffs to Orrick re Structured Data questions
Aug 20, 2016 Ltr from Plaintiffs to Orrick re Structured Data
Aug 25, 2016 Ltr from Orrick to Plaintiffs re Structured Data Questions
Aug 26, 2016 Ltr from Plaintiffs to Orrick re Scope of Production
Aug 29, 2016 Ltr from Plaintiffs to Orrick re Structured Data Questions
Aug 30, 2016 Ltr from Plaintiffs to Orrick re HiPo
Sept 6, 2016 Ltr from Plaintiffs to Orrick re Structured Data questions
Sept 9, 2016 Ltr from Orrick to Plaintiffs re Structured Data questions

Sept 13, 2016 Ltr from Plaintiffs to Orrick re Structured Data questions
Sept 16, 2016 Email from Plaintiffs to Orrick (Subject: RE Moussouris Correspondence regarding meet and confer questions data/ production)
Sept 21, 2016 Ltr from Orrick to Plaintiffs re Structured Data questions
Sept 22, 2016 Ltr from Plaintiffs to Orrick re HiPo and Structured Data questions
Sept 30, 2016 Ltr from Orrick to Plaintiffs
Oct 3, 2016 Ltr from Plaintiffs to Orrick
Oct 6, 2016 Ltr from Orrick to Plaintiffs
Oct 10, 2016 Ltr from Plaintiffs to Orrick
Oct 12, 2016 Ltr from Plaintiffs to Orrick
Oct 13, 2016 Ltr from Orrick to Plaintiffs
Oct 13, 2016 Ltr from Plaintiffs to Orrick (2)
Oct 13, 2016 Ltr from Plaintiffs to Orrick
Oct 24, 2016 Ltr from Plaintiffs to Orrick
Oct 26, 2016 Ltr from Orrick to Plaintiffs
Oct 26, 2016 Ltr from Plaintiffs to Orrick
Nov 2, 2016 Ltr from Plaintiffs to Orrick
Nov 4, 2016 Email from Orrick to Plaintiffs, Subject: Moussouris v Microsoft
Nov 8, 2016 Ltr from Plaintiffs to Orrick
Nov 10, 2016 Ltr from Orrick to Plaintiffs
Nov 14, 2016 Ltr from Plaintiffs to Orrick
Nov 17, 2016 Ltr from Plaintiffs to Orrick
Nov 22, 2016 Ltr from Plaintiffs to Orrick
Dec 6, 2016 Ltr from Orrick to Plaintiffs
Dec 6, 2016 Ltr from Plaintiffs to Orrick
Dec 8, 2016 Ltr from Orrick to Plaintiffs
Dec 12, 2016 Ltr from Plaintiffs to Orrick re Structured Data and Attachment
Dec 14, 2016 Ltr from Plaintiffs to Orrick re Structured Data
Dec 16, 2016 Ltr from Orrick to Plaintiffs
Dec 16, 2016 Ltr from Plaintiffs to Orrick re Meet and Confer
Dec 16, 2016 Ltr (Second) from Orrick to Plaintiffs
Dec 22, 2016 Ltr from Plaintiffs to Orrick re structured data
Jan 13, 2017 Ltr from Orrick to Plaintiffs
Jan 17, 2017 Ltr from Plaintiffs to Orrick
Jan 20, 2017 Ltr from Orrick to Plaintiffs
Mar 13, 2017 Ltr from Orrick to Plaintiffs
Mar 21, 2017 Ltr from Orrick to Plaintiffs re MS People Export
Mar 28, 2017 Ltr from Plaintiffs to Orrick
May 1, 2017 Ltr from Orrick to Plaintiffs
May 24, 2017 Ltr from Plaintiffs to Orrick

June 6, 2017 Ltr from Orrick to Plaintiffs
Sept 14, 2017 Ltr from Plaintiffs to Orrick (OGDMS_1285023_1.pdf)
Sept 21, 2017 Ltr from Plaintiffs to Orrick (OGDMS_1287257_1.pdf)
Oct 16, 2017 Ltr from Orrick to Plaintiffs re Structured Data

III. Court Documents

2015.09.16 DE 001 Class Action Complaint
2016.01.29 DE 048 Stipulated Protective Order
2016.04.06 DE 055 Second Amended Class Action Complaint
2017.10.27 DE 228 Plaintiffs' Motion for Class Certification
2017.10.27 DE 228-1 [Proposed] Order Granting Motion for Class Certification

IV. Declarations, Depositions and Exhibits

2016.01.24 Declaration of Martin Loughlin
2016.01.24 Declaration of Shreejit Sugathan
2016.01.25 Declaration of Larissa Johnson
2016.05.02 Declaration of Larrissa Johnson
2016.05.02 Declaration of Martin Loughlin
2016.05.06 Declaration of Shreejit Sugathan
2016.05.09 Declaration of Joe Whittinghill and Exhibits A-D
2016.05.10 Deposition 30(b)(6) of Joe Whittinghill and Exhibits 1-13
2016.05.11 Deposition of M. Loughlin and Exhibits 1-6
    2016.06.20 Loughlin Errata Sheet for 2016.05.11 Deposition
2016.05.12 Deposition of Larrissa Johnson and Exhibits 1-5
2016.05.12 Deposition of Shreejit Sugathan and Exhibits 1-3
2016.06.09 Deposition of Dana Piermarini
2016.06.10 Deposition of Katherine Moussouris
2016.06.29 Deposition 30(b)(6) of John Ritchie, Volume I and Exhibits 1-25
2016.06.30 Deposition 30(b)(6) of John Ritchie, Volume II and Exhibits 26-48
2016.12.07 Deposition 30(b)(6) of Amy Coleman and Exhibits 1-8
2017.04.10 DE 172 Declaration of Dev Stahlkopf ISO Oppo to Pls Mot to Compel FUS
2017.04.10 DE 174 Declaration of Kris Meade ISO Oppo to Pls Mot to Compel FUS
2017.10.27 DE 233 Declaration of Shaver ISO Mot for Class Certification & Exhibits A-H
2017.10.27 DE 234 Declaration of Kelly Dermody ISO Mot for Class Certification & Exhibit A
2017.10.27 DE 235 Declaration of Adam Klein ISO Mot for Class Certification
2017.10.27 DE 236 Declaration of Michael Subit ISO Mot for Class Certification
2017.10.27 DE 237 Declaration of Amy Alberts
2017.10.27 DE 238 Declaration of Heidi Boeh

2017.10.27 DE 239 Declaration of Debra Dove
2017.10.27 DE 240 Declaration of Olga Hutson
2017.10.27 DE 241 Declaration of Laura Miller
2017.10.27 DE 242 Declaration of Katherine Moussouris
2017.10.27 DE 243 Declaration of Holly Meunchow
2017.10.27 DE 244 Declaration of Mary Smith
2017.10.27 DE 245 Declaration of Suzanne Sowinska
2017.10.27 DE 246 Declaration of Jennifer Underwood
2017.10.27 DE 247 Declaration of Lanen Vaughn
2017.10.27 DE 248 Declaration of Kristen Warren
2017.12.08 Deposition of Henry S. Farber, Ph.D.

V. Dr. Farber's Materials

a. Expert Report and Errata

Expert Report in the Matter of *Moussouris v.* Microsoft Submitted by Henry S. Farber, Ph.D. (Oct. 27, 2017)
Corrected Expert Report in the Matter of *Moussouris v.* Microsoft Submitted by Henry S. Farber, Ph.D. (Dec. 5, 2017)
Errata_Table_signed (Dec. 5, 2017)
Stipulation and [Proposed] Order Regarding Corrected Expert Report of Dr. Henry S. Farber in Support of Plaintiffs' Motion for Class Certification (OGDMS_1323534_2)

b. Backup Programs

advancement
advancement_table_sl
bprobit_sl
Calculate Total Class Compensation
HowManyClassMembers
import Oct24 production
import supplemental MSFT
microsoft_analysis
microsoft_analysis_addendum
missing_education
MSFT_Histograms_For_October2017_Report
MSFT_Tables_For_October2017_Report
advancement_errata
advancement_table_errata
bprobit_sl_errata

MSFT_Histograms_For_October2017_Report_errata

VI. Articles and Papers

Abowd, J., F. Kramarz and D. Margolis (1999) “High Wage Workers And High Wage Firms,” *Econometrica*, pp. 251–334.

Becker, Gary S. *Human Capital*, 1964, 2nd Edition, New York, NY: National Bureau of Economic Research.

Bertrand, Marianne, Claudia Goldin, and Lawrence F. Katz. "Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors." *American Economic Journal*. Applied Economics 2, no. 3 (2010): 228.

Blau, Francine D., and Lawrence M. Kahn. "The gender wage gap: Extent, trends, and explanations." *Journal of Economic Literature* 55, no. 3 (2017): 789-865.

Farber, Henry, “Union Wages and the Minimum Wage,” MIT Econ Dept Working Paper No. 278, Feb. 1981, p. 14. Published in *Report of the Minimum Wage Study Commission*. Vol. VI, 105-134.

Goldin, Claudia. "A grand gender convergence: Its last chapter." *The American Economic Review,* 104, no. 4 (2014): 1091-1119.

Goldin, C. and L.F. Katz, “Technology, Skill, And The Wage Structure: Insights From The Past,” *American Economic Review*, May 86 (1996) (2), pp. 252–257.

Greene, W. (1993) *Econometric Analysis*, 2nd Edition, NY: Macmillan Publishing Company.

Griliches, Z. (1977) “Estimating the Returns to Schooling: Some Econometric Problems,” *Econometrica*, 45:1-22.

Haltiwanger, J., J. Lane and J. Spletzer (June 2007) “Wages, Productivity, And The Dynamic Interaction Of Businesses And Workers,” *Labour Economics*, 14(3), pp. 575-602

Hunt, Jennifer, Jean-Philippe Garant, Hannah Herman, and David J. Munroe. “Why don't women patent?” No. w17888. National Bureau of Economic Research, 2012.

Killingsworth, Mark R., and James J. Heckman. "Female labor supply: A survey." *Handbook of Labor Economics* 1 (1986): 103-204.

Leamer, Edward, *Specification Searches: Ad Hoc Inferences with Non-Experimental Data*, New York, Wiley, 1978.

McCloskey, Donald N., “The Loss Function Has Been Mislaid: The Rhetoric of Significance Tests,” *American Economic Review Papers and Proceedings*, May 1985, pp. 201-205.

Mincer, Jacob (1958). Investment in Human Capital and Personal Income Distribution. *Journal of Political Economy* 66 (4): pp. 281-302.

Mincer, Jacob, "On-the-Job Training: Costs, Returns, and Some Implications," *Journal of Political Economy*, Supplement to Vol. 70, 1962.

Mincer, Jacob (1974). *Schooling, Experience and Earnings*. New York, National Bureau of Economic Research; distributed by Columbia University Press.

Piette, Michael J. and Paul F. White, "Approaches for Dealing with Small Sample Sizes in Employment Discrimination Litigation," *Journal of Forensic Economics* 12(1), 1999, pp. 43-56.

Rubenfeld, Daniel. "Reference Guide on Multiple Regression," *Reference Manual on Scientific Evidence: Third Edition*, page 318.

Willis, R. (1986) "Wage Determinants: A Survey and Reinterpretation of Human Capital Earnings Functions," Chapter 10, *Handbook of Labor Economics, Volume 1*, Edited by O. Ashenfelter and R. Layard. Elsevier Science Publishers BV: 525-602.

VII. Other

2016.05.18 Plaintiff Holly Muenchow's Amended Objections and Responses to Defendant Microsoft Corporation's First Set of Interrogatories to Plaintiff Holly Muenchow

2016.05.19 Plaintiffs' Second Set of Requests for Production of Documents

2016.06.02 Plaintiff Katherine Moussouris' Objections and Responses to Defendant Microsoft Corporation's First Set of Interrogatories to Plaintiff Katherine Moussouris

Expert Report in the Matter of *Moussouris v.* Microsoft Submitted by Ann Marie Ryan, Ph.D. (Oct. 26, 2017)

Expert Report of Henry S. Farber, In Connection With *Chen-Oster v. Goldman Sachs*, S.D.N.Y. No. 10-6950, DE 259 (Feb. 17, 2014)

American Community Survey (ACS) PUMS Data: https://www.census.gov/programs-surveys/acs/data/pums.html

EEOC Uniform Guidelines on Employee Selection Procedures: Adoption of Questions and Answers To Clarify and Provide a Common Interpretation of the Uniform Guidelines on Employee Selection, Federal Register, Vol. 44, No. 43, March 2, 1979: https://www.eeoc.gov/policy/docs/qanda_clarify_procedures.html

Microsoft's US Security and Exchange Commission Form 10-K filings, 2012 and 2016:
https://www.sec.gov/Archives/edgar/data/789019/000119312512316848/d347676d10k.htm
https://www.sec.gov/Archives/edgar/data/789019/000119312516662209/d187868d10k.htm